ASSESSMENT OF POWER QUALITY EVENTS BY HILBERT TRANSFORM BASED NEURAL NETWORK

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ASSESSMENT OF POWER QUALITY EVENTS BY HILBERT TRANSFORM BASED NEURAL NETWORK

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By

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Dedicated to my beloved parents
And brother

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CERTIFICATE

This is to certify that the dissertation entitled **"Assessment of Power Quality Events by Hilbert Transform based Neural Network"** being submitted by **Mr. Shyama Sundar Padhi** bearing Roll No. 213EE4331, in partial fulfillment of the requirements for the award of degree of **Master of Technology in Electrical Engineering** with Specialization **"Power Electronics & Drives"** during session 2014-2015 at the **National Institute of Technology**, **Rourkela**, is a bonafide record of work carried out by him under my guidance and supervision.

The candidates have fulfilled all the prescribed requirements.

Date:

Place: Rourkela

Prof. Sanjeeb Mohanty

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National Institute of Technology

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ABSTRACT

Now a day's power quality (PQ) and power supply related problems have become important problem both for the end user and the utility company. The PQ issues and related phenomena are getting more dominant due to the use of power electronics devices, non-linear loads, industrial grade rectifiers and inverters, etc. This nonlinear equipment's not only introduce distortions in the amplitude but also in frequency, phase of the power signal, thereby degrades quality of power. In order to improve power quality, continuous monitoring of the signal is required. For continuous monitoring of the signal, the detection and classification of the power signal in power systems are important. In this work a new Time-frequency analysis method, has been introduced to detect and analyze for the non-stationary and nonlinear power system disturbance signals, known as Hilbert-Huang transform (HHT). Hilbert-Huang transform is able to find out, the starting time, ending time, instantaneous frequency-time, and instantaneous amplitude- time of the disturbance signal can be obtained precisely. Hilbert Huang transforms decomposition algorithm can be used for accurate detection & localization of point of disturbance of PQ events like voltage sag, swell, sag with harmonic, swell with harmonic, interruption, etc. Similarly the same power quality event was passed through a wavelet technique. Both results are obtained from decomposition of PQ events and pass through a back propagation neural network for proper classification of different types of PQ events.

In this work, detection of PQ disturbances by HHT is compared with an advance wavelet transform technique. The localization and detection of PQ events have been thoroughly investigated for each of the power signal disturbances using HHT and wavelet transform. Finally, comparative classification accuracy has been estimated for both types of the decomposition technique for different types of PQ events.

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ACRONYMS

ANN	Artificial Neural Network
NN	Neural network
WT	Wavelet Transform
BPA	Back-propagation algorithm
MSE	Mean square error
HHT	Hilbert Huang Transform
EMD	Empirical Mode Decomposition
MFFN	Multilayer Feed Forward
FT	Fourier Transform
IF	Instantaneous Frequency
IA	Instantaneous Amplitude
MODWT	Maximum Overlap Decomposition wavelet Technique
MFFN	Multilayer Feed Forward Network

CHAPTER # 1

Introduction

1.1 Background

In late 1980's the Power Quality (PQ) becomes a major concern for recent power industries and research field. Due to the use of automated control equipment's in industry, it becomes necessary for a power engineer continuous monitoring of the power signal increased and continuous control of power system equipment is required. The power quality (PQ) includes disturbances both of current and voltage like voltage swell, sags, harmonics, and oscillatory transients which cause malfunction of power equipment. Hence Power quality may be defined as "nonstop deviation of voltage, current and/or frequency in time". For smooth operation of power system, the proper maintenance of equipment as well as good power quality is required. The main cause of PQ disturbance is the power-line disturbances. The PQ disturbance leads to decrease in life span, permanent failure electrical equipment. PQ has direct economic impacts on many industrial consumers. A lot of emphasis has been given on revitalizing industry with lots of automation and modern engineering equipment. The Power utility company always trying to maintain customer confidence and make them strong motivators.

The power quality events monitoring requires signal processing technique and artificial intelligence techniques are used to examine detection, compression, and classifications of power quality disturbances. These techniques are typically applied to the spectral analysis of monitoring signals, in estimation of power quality indices. For power quality characterization, the accurate detection of PQ disturbances is the primary and most important steps of monitoring. Insufficiency of proper power leads either to malfunction or permanent failure of electrical equipment's. The power quality issues are caused by

- Use of semiconductor devices
- Nonlinear loads
- Lighting controls
- Capacitor switching

- Industrial plant loads like rectifiers and inverters

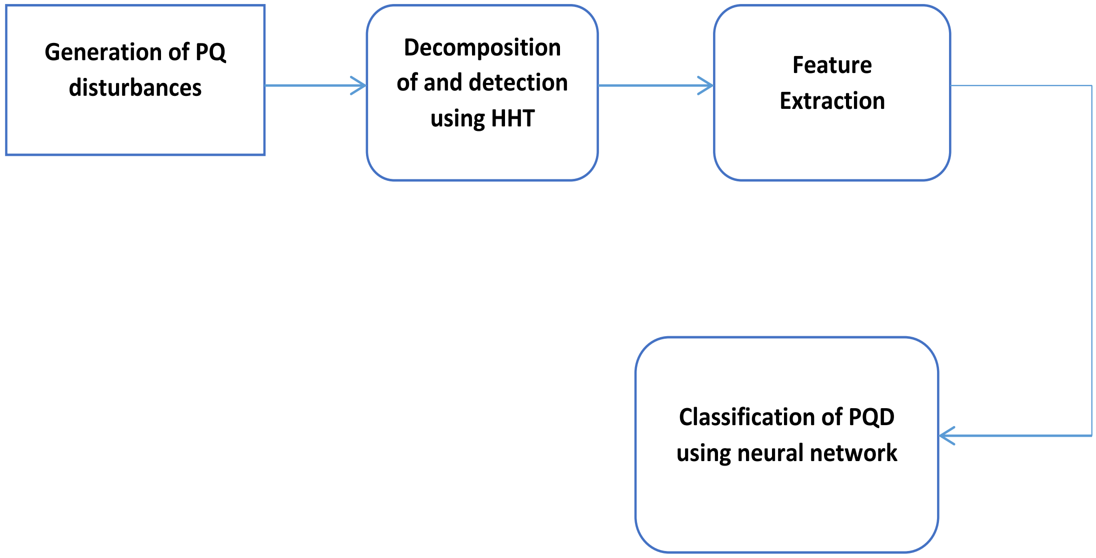


Fig.1.1 Basic block diagram of the method adopted

The fig. 1.1 demonstrates the essential sectional form of the complete PQD recognition and arrangement technique. In the first stage the seven different power quality disturbances are generated using parametric equations. In the second stage, the signals are decomposed through Empirical mode decomposition and Hilbert transforms. Hence, instant or point of disturbance is detected. In the fourth stage the features like standard deviation, energy and entropy of the signal are extracted from the detected noise free signal. In the fifth and final stage the above mentioned features are used to classify different PQ disturbances using a PQD detection system using multilayer Feed forward neural network.

1.2 Literature review:

To improve power quality, a lot of research has been done in order to find out the sources of PQ disturbances and search for a solution to mitigate them. The electric power quality disturbance monitoring has been achieved by many detection techniques like Wavelet transformation (WT), Fourier transforms and stockwell transform (S-transform) etc. [1]. The Fourier transforms (FT) technique is widely used frequency domain technique which provides information about harmonic and harmonic associated signal to be monitored [2]. FT distinguishes the diverse recurrence sinusoids and their individual amplitudes which consolidate to frame a discretionary waveform. However FT is known as the quickest system, yet it is constrained to just to stationary signals [3]. Short time discrete Fourier transform (STFT) is the improved form of FT technique and most often used. The main advantage of STFT transform is that it can be successfully used for stationary signals where properties of signals do not evolve in time [4]. But in case of non-stationary signals, the short time discrete Fourier transform does not track the signal disturbances properly due to the limitations of a fixed window width chosen a prior. However the major disadvantage of STFT technique is that it needs substantial amount of computational resources. Thus, the STFT is not suitable for use to analyze transient signals comprising both high and low-frequency components.

Stockwell transform commonly known as the S-transform (ST) is a technique which is being widely used by PQ researchers [5]. The ST is an extension of WT is based on localizing the Gaussian window. Here, the modulating sinusoids are fixed with respect to the time axis while the Gaussian window scales and moves [6]. The wavelet transform technique is also suitable time-scale analysis technique used for feature extraction of stationary as well as non-stationary power system signal. Wavelet transform like its discrete version (i.e. DWT) and its advance version are suitable technique used for the analysis of non- stationary disturbances in the electrical power network [8]. The wavelet transform (WT) provides time and frequency information of the signal by convolving the enlarge and translated wavelet with the signal. The main disadvantage of WT is that it degrades performance under noisy situation [9]. Anyway, the greater part of the PQ event is non-stationary and thus there is need of such strategy which would give recurrence data as well as find the timing of events of the unsettling impact.

A new Time-frequency method has been developed for nonlinear and non-stationary signal analysis known as Hilbert-Huang transform. This transformation technique provides information about the frequency components occurring at any specified time [11]. This advance technique comprises of two parts, one part is the empirical mode decomposition (EMD) and another one is a Hilbert transform for assessment of power quality events. A distorted waveform can be considered as superimposition of various oscillating modes and EMD is used to separate out these intrinsic modes known as intrinsic mode functions (IMF). Hilbert transform is always applied to first three IMF of the signal to obtain instantaneous amplitude and phase. This is because first three IMF contains all the meaningful information. Than this instantaneous attributes form a feature vector [12].

1.3 Motivation

In modern ages the quality of power has become a substantial issue for deregulated power system. Therefore the power quality in the modern power industry becomes a challenge to the power system engineer. The major reason behind the concern over power quality is the economic value. There is a substantial impact on economic impact on utilities, their costumer and manufacturer of electrical load equipment. Industries keep on emphasizing on the use of more efficient, automatic and modern equipment. That means electronically controlled, energy- efficient equipment are very sensitive towards the deviation of supply voltage. However the residential customers don't suffer direct financial loss as a result of power quality issue, but these costumers are very sensitive towards the home appliances like computer and other electronically operated devices which gets interrupted because of PQ issue.In order to improve quality of power, the different sources and reasons of these disturbances must be known before proper mitigation. However, in order to find out the causes and sources of disturbances, someone must have good knowledge of detection and localization these disturbances. For maintenance good power quality, continuous monitoring of the signal is required and it can also provide the point of disturbance. The PQ disturbance causes malfunction, reduction of life span and permanent failure of equipment, and also leads to economic losses. PQ disturbances cannot be completely mitigated but it can be reduced to some extent by proper continuous monitoring. Reduction of PQ disturbances has been main attraction in the modern engineering field which motivates me to carry out this project work.

1.4 Objectives:

The main objectives of this work involves the following processes

- To generate different power quality disturbances using parametric equations
- New Time-frequency signal detection technique has been introduced known as Hilbert Huang Transform (HHT). HHT consisting of two parts
  - Empirical Mode Decomposition
  - Hilbert transforms
- To classify the power quality events using a Feed Forward Neural Network technique.
- To present a Comparative study between HHT technique and wavelet transform (MODWT) technique.

1.5 Thesis Layout

Chapter 1 gives a detailed overview on various power quality issues and characterization of power quality disturbances. The Literatures are also reviewed on the Hilbert Huang transform as a tool for analyzing different power quality events in association with the artificial neural network technique. The Motivation as well as objective, briefly described about the work is presented in this chapter.

Chapter 2 describes the feature extraction procedure of Hilbert Huang transform. Here different types of power quality events are generated using parametric equations and the signals are decomposed using EMD decomposition algorithms and Hilbert transform. Different IMF functions are obtained from EMD and Hilbert spectrums are plotted. The same power signal has been decomposed through wavelet transform.

Chapter 3 describes about different features vector which is applied as input data for training purposes. Hence the mean square error (MSE) vs. time and Mean Absolute Error (MAE) vs. time were obtained. The classification accuracy of PQ events was estimated by using Multilayer Feed Forward Neural Network (MFNN).

Chapter 4 described about the overall Conclusion of the work. Here future work explains about the extension of work may be carried out.

CHAPTER # 2

Discrete Signal Processing techniques

2.1 Hilbert Huang transform over Wavelet transform

Hilbert Huang transforms convert time domain data (here power system signal data) into frequency at different scale and in terms of position. Hilbert Huang transform is the combination of EMD and HT. So the power system signal finds for the intrinsic oscillatory mode, which forms intrinsic mode functions. These IMFs is the best suitable for signal decomposition more accurately. Generally Time domain analyses are not required when the signal is stationary. Hilbert Huang transform is time-frequency analysis technique which is used for analyzing a stationary signal as well non stationary signal and nonlinear signal that decomposes the signal into different intrinsic mode functions (IMF). Whereas it is known that Wavelet transforms can be used to analyze a non-stationary signal, but can't be used for nonlinear signal. One of the major differences between Hilbert transform analysis and wavelet transform is that, HHT provides self-adaptive and does not work on the predefined functions unlike wavelet functions are already defined. Hilbert transforms, analysis gives local representation (in time and frequency) of the signal. Wavelet transform (WT) can provide a time-scale representation of any non-stationary waveforms without losing any time- or frequency-related information. The commonality between wavelet and Hilbert transform is both gives local representation (in time and frequency) of the signal. Wavelet transformation works on the basis of forward transformation where the transformation occurs from time domain to time scale domain. WT uses the scaled and offset for the forms of limited duration, irregular and asymmetric signal pieces, which is called the mother wavelet [12]. A signal can be analyzed better with an irregular signal pieces. The main disadvantage of WT is its degraded performance under noisy situation. The empirical mode decomposition (EMD) and the Hilbert transform (HT) are labeled as HHT [9]. A signal is passed through the EMD method which decomposes the signal into number of intrinsic mode functions (IMFs). The decomposition is based on the direct extraction of the energy associated with various intrinsic time scales or level, the most important parameters of the system. Instantaneous attributes can be obtained from Hilbert transform which is commonly used to generate an analytic signal. Since Hilbert transform analysis is based on transfer function i.e. Discrete Fourier transforms

(DFT), it gives rise to the spectral content of the signal. Therefore, HHT is a very suitable technique for non-stationary signal.

2.1.1 Application of Hilbert Huang transforms

Since Hilbert Huang transform is based on a local characteristic time scale, it finds a wide range of areas, such as

- ✓ Discrimination of seizure and seizure free ECG signal in biomedical application
- ✓ Fingerprint verification
- ✓ Neural Science
- ✓ Finance application
- ✓ Speech recognition
- ✓ Chemistry and chemical engineering
- ✓ Ocean engineering, etc.

2.2 Empirical Mode Decomposition

N.E Huang et al. (1996, 1998, and 1999) developed the Empirical Mode decomposition technique which found to be useful for nonlinear and non-stationary the data analysis. In contrary to all traditional detection technique this new method is direct, simple and adaptive method. The HHT technique comprises of two phases, first phase is the empirical mode decomposition (EMD) and a second phase is Hilbert spectral analysis (HAS) or Hilbert transform.

The first phase of HHT that is the Empirical mode decomposition (EMD) is a data analysis method which separates out the different distorted superimposed waveform and generates a series of intrinsic mode functions (IMFs). However first three IMFs are used for feature vector extraction. This decomposition method extracts energy associated with various intrinsic mode functions which are the important parameters for further analysis and obtaining information about the signal system. The generalized concept behind EMD is that it assumes any data consist of number of IMF functions.

The Pure sinusoidal waveform has a constant frequency and properly defined quantity. But in actual power signal signals are not pure sinusoidal or stationary. Hence, any power system non stationary signal is a combination of a number of sinusoidal components. Such non stationary nature of signal frequency loses its practical importance and looks for the different phenomena. There it introduces the concept of instantaneous frequency (IF). The instantaneous frequency of a signal may either comprise of single frequency or small band of frequency. This requirement leads to a new concept of separating different components of a signal such that each component of instantaneous frequency can be defined. An IMF can be treated as a simple oscillatory mode of simple harmonic function. But the IMF has an amplitude and frequency which is a function of time, but in the case of simple harmonic components; amplitude and frequency are constant term.

2.2.1 Features of EMD

- EMD method is very sensitive to noisy signal in power signal.
- EMD method is flexible and robust because IMF are generated from the signal itself rather than defined earlier.
- It is highly efficient in nonlinear signal and suitable for non-stationary data analysis technique.
- It is carried out in the time domain since it can be provided as time-frequency analysis.
- The IMF has both amplitude and frequency modulated.

2.2.2 Assumptions considered in EMD

1. Any power system signal must have at least one maximum and one minima.
2. The time lapse between the extreme points can be characterized as time scale.
3. If the data is totally deviates from extreme values but contained only inflection points, then it can be differentiated once or more times to reveal the extreme. Final results then can be obtained by integration(s) of the components.

2.2.3 An IMF function must satisfy two conditions

1) For analysis of a signal, the number of extreme and the number of zero crossings must either be equal or their maximum difference should be one.
2) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

2.3 Steps for EMD method

An IMF function is much more general than an oscillatory mode because it has variable amplitude and frequency as a function of time. According to the definition of the IMF, we can decompose any function as follows and Fig.2.1 shows the algorithm of EMD.

(1) At First, it is required to find out all the local maxima pints of x (t).

(2) Interpolate (cubic spline fitting) between all the maximum points, ending up with some upper envelope e_{max} (t).

(3) Then find out all the local minima points.

(4) Interpolation (cubic spline fitting) of all the minima points, ending up with some lower envelope e_{min} (t).

(5) Now calculate the mean envelope between upper envelope and lower envelope is given as

$$m_1 = \frac{e_{min}(t)+e_{max}(t)}{2} \tag{2.1}$$

(6) Residue is computed as given below

$$\mathrm{r_1 = x(t) - m_1} \tag{2.2}$$

(7) A critical decision is made based on the stopping criterion. If this squared difference is smaller than a predetermined threshold, the sifting process will be stopped. The threshold is calculated by the following formula:-

$$SD_k = \sum_{t=0}^{T} \frac{|(r_{1(k-1)}(t)-r_{1k}(t)|^2}{r_{1(k-1)}^2(t)} \tag{2.3}$$

$$\mathbf{0.2 \leq \mathit{SD} \leq 0.3}$$

2.4 Algorithm of EMD

The algorithm of the Empirical Mode decomposition has been shown in the fig.2.1.

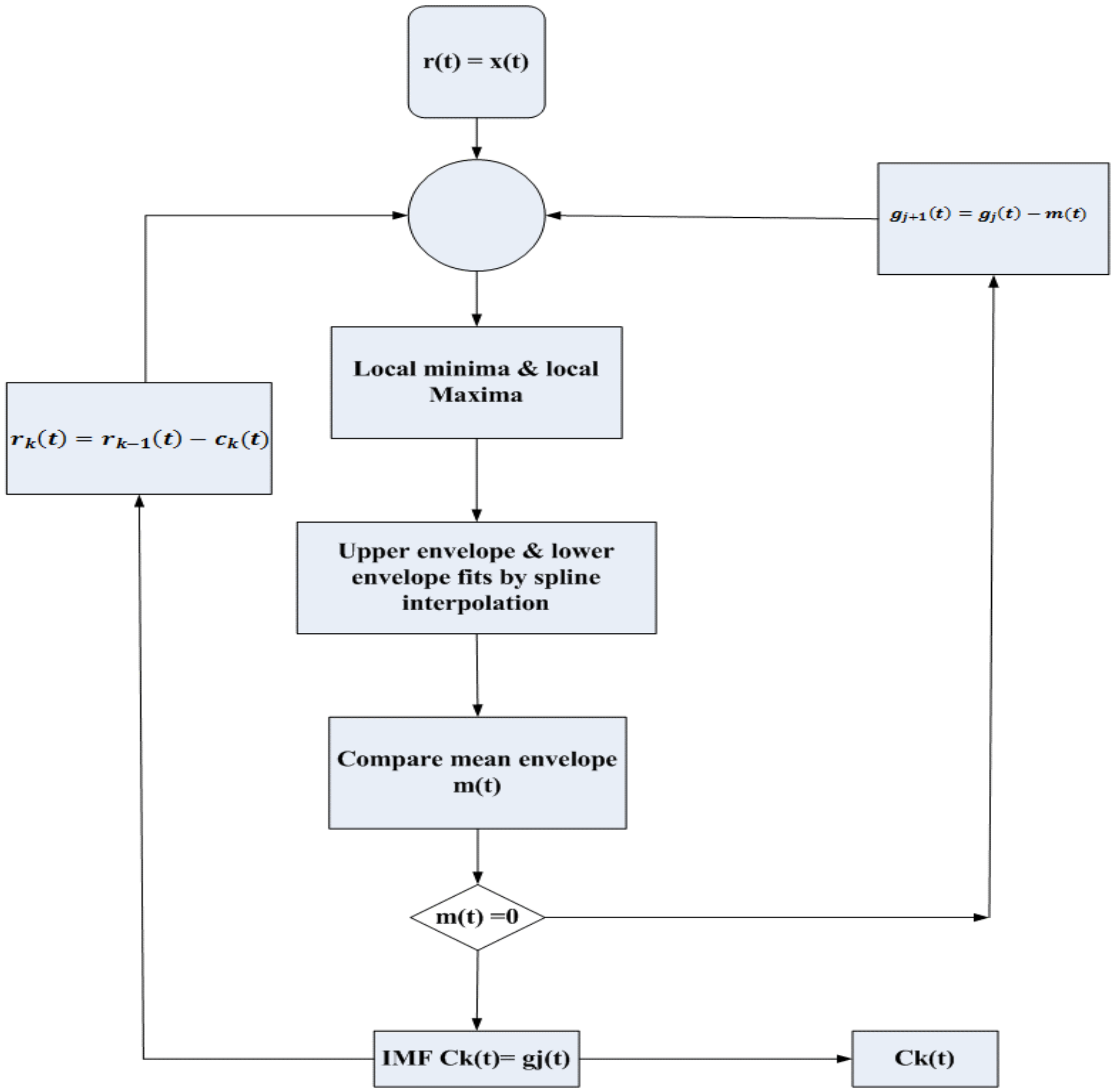


Fig.2.1 EMD algorithm

2.5 Hilbert transforms

According to signal processing and mathematics, Hilbert transforms can be defined for the function x (t) as H (x)(t), with the same domain. Hilbert transform is generally used in a control system. The Hilbert transform was developed by David Hilbert, in order to solve a certain special case of the

Riemann–Hilbert problem for holomorphic functions. It is a based on Fourier analysis, which gives a concrete means for realizing the harmonic conjugate of a given function or Fourier series. In this work Hilbert transform has been used for converting the power system signal from the time domain into the frequency domain. Furthermore, in harmonic analysis, it is useful to derive an analytic representation of a signal by using Fourier multiplier. The Hilbert transform is also useful in the field of signal processing where it is used to derive the analytic representation of a signal x (t).

Important Feature on Hilbert transforms

- Hilbert transform is helpful in calculating instantaneous attributes of a time series, which is the amplitude and frequency. The instantaneous amplitude is the amplitude of the complex Hilbert transforms; the instantaneous frequency is the time rate of change of the instantaneous phase angle.
- Complex signals are important, because they offer an opportunity to calculate instantaneous, amplitude and frequency, energy. That is why complex signals are known as 'analytic signals'. The signal can be analyzed sample-wise instead of frame-wise, and sometimes such fast access to analysis is welcome.
- In or to derive an analytic signal from a real signal, a "$-\frac{\pi}{2}$" radian phase shifted version of the real signal must be made, an imaginary phase. The imaginary phase signal is known as quadrature phase, because π/2 radians make a square angle of the complex plane.
- The German mathematician David Hilbert, developed the mathematics of the transform, which was title as Hilbert Transform is given by

$$z(t) = x(t) + j.y(t) = a(t).e^{j\theta(t)} \tag{2.4}$$

Where instantaneous amplitude a (t) and phase θ (t) in (3) can be estimated using Euler's formula.

These instantaneous amplitude and phase are useful for harmonic analysis only when x (t) is a monotonic signal.

2.6 Hilbert Transform Analysis

Hilbert Transform is generally used to generate a complex Frequency series from a time series or analytic signal. The benefit is that instantaneous attributes can be derived from complex traces.

However, accurate and meaningful computation of these attributes requires that the input signal's start and end have zero amplitude and it contains no trend that introduces a nonzero mean. In this regard, perhaps the most significant use for the EMD is to prepare a signal for input to the HT.

The method for computing the discrete HT is based upon its transfer function and utilizing the discrete Fourier transform (DFT) as a tool. The frequency of a sinusoidal signal is always well defined, but in case of non- stationary signal it loses its effectiveness. Therefore, it gives rise to instantaneous frequency.

The Hilbert transform of $u(t)$can be written as the convolution of $u(t)$ with the function $h(t)=1/\pi t$. Because $u(t)$is not integration-able the integrals defining the convolution do not converge. Instead, the Hilbert transform is defined using the Cauchy principal value explicitly, the Hilbert transform of a function or signal *u (t)* is given by

$$h(u) = \mathrm{p.v.} \int_{-\infty}^{\infty} u(\tau).h(t-\tau).d\tau = \frac{1}{\Pi}\, p.v. \int_{-\infty}^{\infty} \frac{u(\tau)}{t-\tau} d\tau$$

The mathematical expression for instantaneous amplitude is given as

$$z(t) = x(t) + j.y(t) = a(t).e^{j\theta(t)} \tag{2.5}$$

Where *a (t)* and *φ (t)* are the amplitude and phase, respectively. In Eq. (3) and θ *(t)* are defined as following:

The instantaneous frequency can be given by Instantaneous frequency $= \dfrac{1}{2\pi}\dfrac{\partial\theta}{\partial(t)}$ (2.6)

$$Phase\ angle\ \theta = tan^{-1}\frac{x_H(t)}{x(t)} \tag{2.7}$$

Where $X_H(t)$ here represents to *H (u) (t)* i.e. Hilbert transform of x (t).

Where *a (t)* and θ *(t)* are the amplitude and phase angle respectively. In Eq. (3) *a (t)* and θ *(t)* are defined as follows:

$$\mathrm{X\ (t)}= Real \sum_{i=1}^{n} a^{j\theta_i(t)}\,(t)\, e^{j\theta_i(t)} \tag{2.8}$$

Here the residue h_1 is eliminated since it is either a monotonic function or it might be smaller than the predetermined threshold.

The analytical signal Z (t) has a real part X (t) which is the original data and imaginary part y (t) which contains the HT .the Hilbert transformed series data has same amplitude and frequency as that of original real data and includes phase information that directly depends on the phase of the original data.

2.7A comparative between Fourier, wavelet and HHT analysis

Table 2.1 shows a comparison between Fourier, Wavelet transform and HHT analysis.

Table 2.1 comparison between Fourier, wavelet and HHT analysis

Fourier	Wavelet	Hilbert
It works based on the predefined functions	It works based on the predefined functions	It is self-Adaptive.
It’s transformed the input through Convolution globally.	It’s transformed the input through Convolution regional.	It finds its attributes by Differentiation: locally.
It gives Energy-frequency representation.	It gives Energy-time –frequency representation.	It gives Energy-time –frequency representation.
It does not work for nonlinear system.	It does not work for nonlinear system.	This technique can be applied for nonlinear system.
It does not work for non-stationary signal.	It works for non-stationary signal.	It works for non-stationary signal.
It is not helpful in extracting features from the signal.	Here are featured extraction is possible.	Here are featured extraction is possible.

2.8 Generation of PQ disturbances

The different types of power quality disturbances like voltage Sag, Swell, Interruption, flicker, harmonics and Sag with harmonics and Swell with harmonics can be generated with different magnitudes using MATLAB equation given in the table 2.1.

2.8.1 Signal specification

T (Time period) =0. 02 Sec, fs (sampling frequency) =3. 2 KHz, f=50Hz, Total Sampling points=614, Duration of disturbance=0. 2 second.

Table 2.2 Power Quality Disturbances Parametric Equations

PQD event	**Equation**
Normal Voltage	$v(t)=\sin(wt)$
Sag	$v(t)=[1-\alpha(u(t-t_1)-u(t-t_2))]\sin(wt)$
Swell	$v(t)=[1+\alpha(u(t-t_1)-u(t-t_2))]\sin(wt)$
Interruption	$v(t)=[1-\alpha(u(t-t_1)-u(t-t_2))]\sin(wt)$
Oscillatory transient	$v(t)=\sin(wt)+\alpha\exp(-(t-t_1)/\tau)(u(t-t_1)-u(t-t_2))\sin(2\pi f_n t)$
Harmonic	$v(t)=\alpha_1\sin(wt)+\alpha_3\sin(3wt)+\alpha_5\sin(5wt)+\alpha_7\sin(7wt)$
Sag with harmonic	$v(t)=[1-\alpha(u(t-t_1)-u(t-t_2))]*\alpha_1\sin(wt)+\alpha_3\sin(3wt)+\alpha_5\sin(5wt)$
Swell with harmonic	$v(t)=[1+\alpha(u(t-t_1)-u(t-t_2))]*\alpha_1\sin(wt)+\alpha_3\sin(3wt)+\alpha_5\sin(5wt)$
Notch	$v(t)=\sin(wt)-sign(\sin(wt))*\{\sum_{n=0}^{9}k*[u(t-(t_1+.02n))-u(t-(t_1+.02n))]\}$
Spike	$v(t)=\sin(wt)+sign(\sin(wt))*\{\sum_{n=0}^{9}k*[u(t-(t_1+.02n))-u(t-(t_1+.02n))]\}$
Flicker	$v(t)=[1+\alpha\sin(2\pi\beta t)]\sin(wt)$

The level of disturbance in each type of disturbances can be varied by using the Parameter ‘α’. The unit step function *u (t)* used in some equation in the above table gives the duration of disturbances present in the pure sine waveform. The disturbed signals are generated by suitably changing the value of α, starting time and ending time in the position of *u (t)* such that a large number of signals can be obtained with varying magnitude. By changing the value of initial time of disturbance t1 and initial time of disturbance t2 one can easily obtain the percentage of disturbance. The harmonic signal involves all second-, third-, fifth- and seventh-order harmonics. The momentary voltage interruption obtained by varying the parameter α for varying the amplitude during the interruption. By using the above parametric model many no. of PQ events of each class of the disturbance can be generated.

2.9 Simulation results & discussion of HHT

2.9.1 Voltage sags signal

The figure 2.2 shows a sag signal with sag staring time t1=0.06 and end time = 0.16. Here the voltage sags signal is passed though empirical mode decomposition (EMD) and four IMF function from IMF1 to IMF4as shown in the fig. 2.2(a) with one residue is obtained. The Instantaneous Amplitude vs. time and instantaneous frequency vs. time (i.e. frequency vs. time) plot has been plotted from fig. 2.2(a) to fig. 2.2(c) by the help of Hilbert transform.

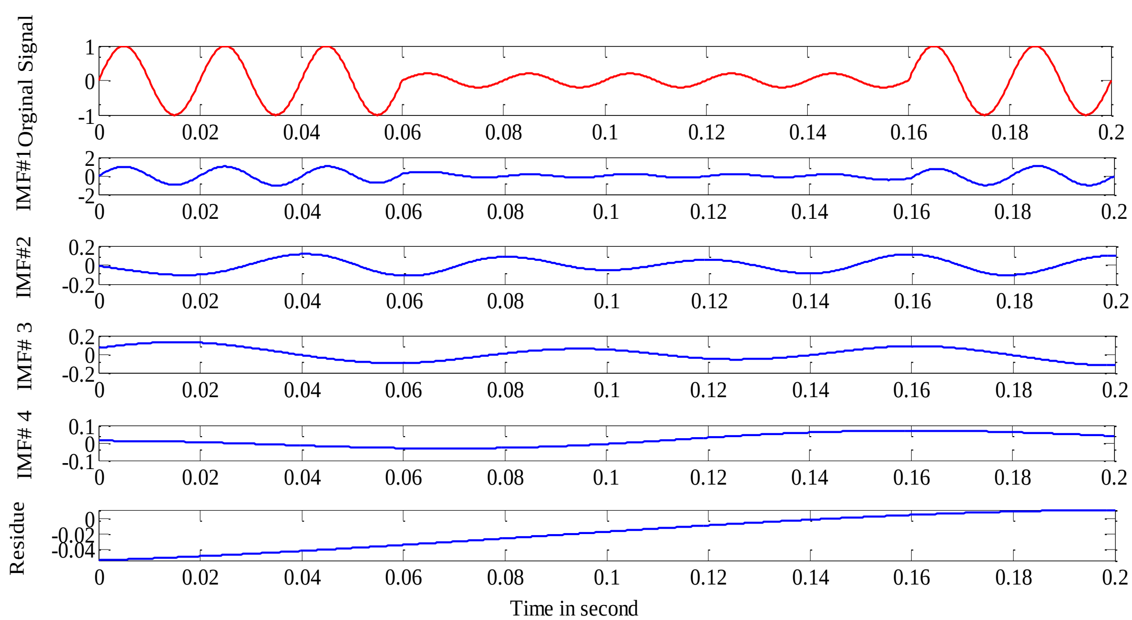


Fig. 2.2 (a) IMF functions of sag signal

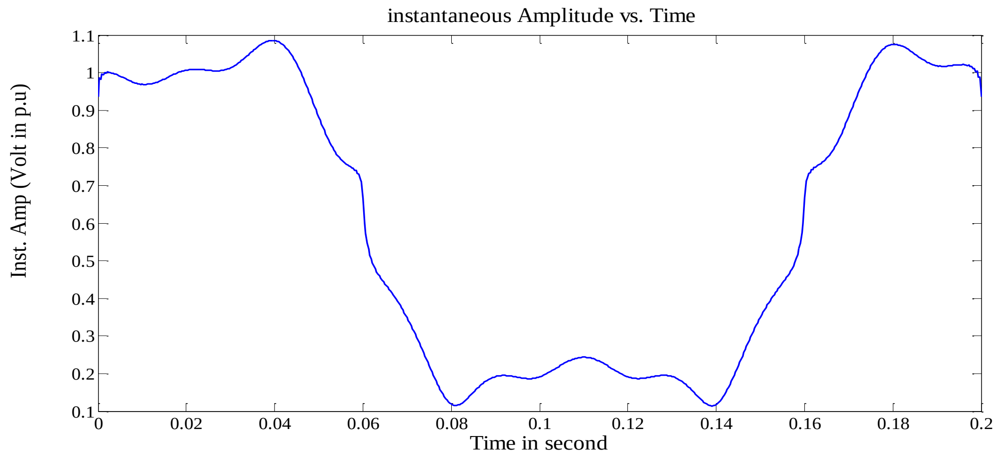


Fig.2.2 (b) Instantaneous Amplitude (IA) Vs. Time of sag signal

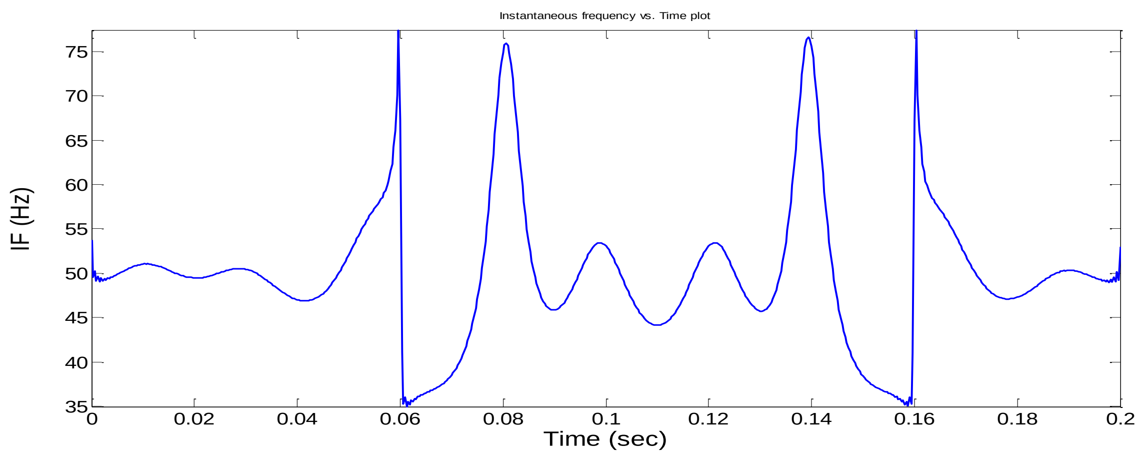


Fig. 2.2 (c) Instantaneous Frequency (IF) vs. time of sags signal

2.9.2 Voltage swells Signal

The figure 2.4 shows a swell signal with sag staring time t1=0.06 and end time = 0.16. Here the voltage sag signal is passed though empirical mode decomposition (EMD) and four IMF function from IMF1 to IMF4as shown in the fig. 2.3(a) with one residue is obtained. The Instantaneous Amplitude vs. time and instantaneous frequency vs. time (i.e. frequency vs. time) plot has been plotted in fig. 2.3(b), fig.2.3(c), fig.2.3 (d) by the help of Hilbert transform.

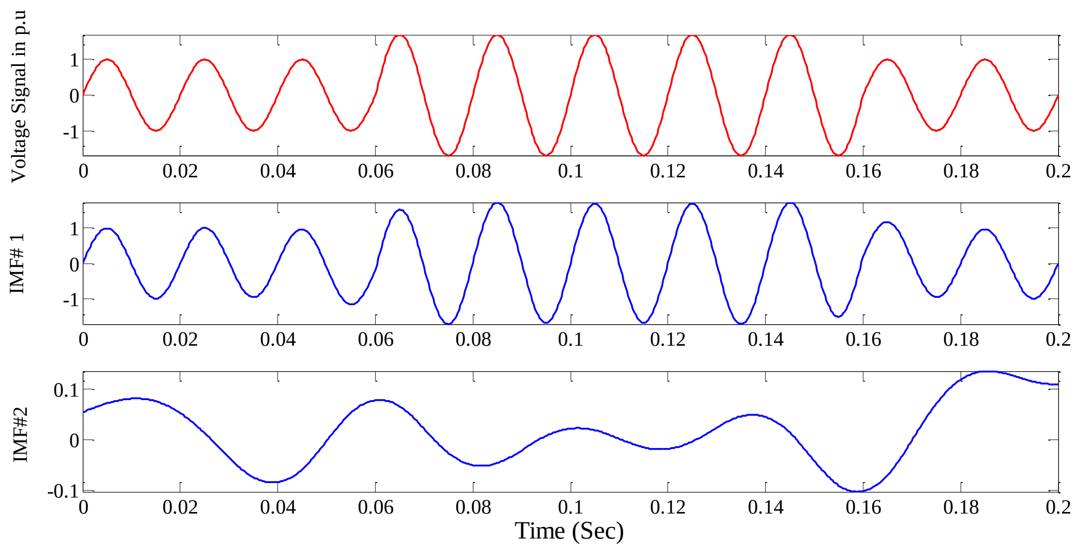


Fig. 2.3 (a) IMF1 & IMF2 functions of swell signal

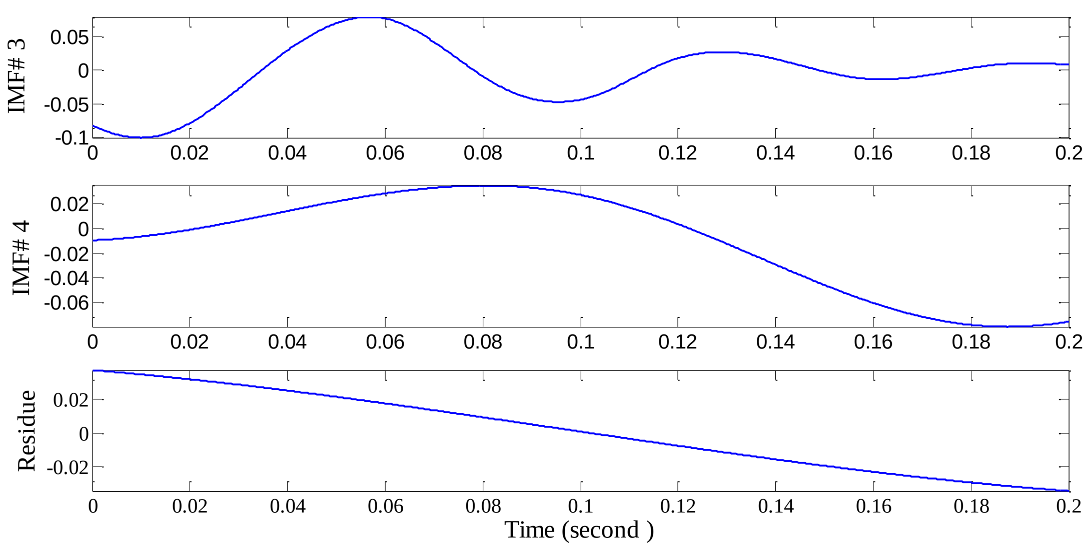


Fig. 2.3(b) IMF3 & IMF4 functions of swell signal

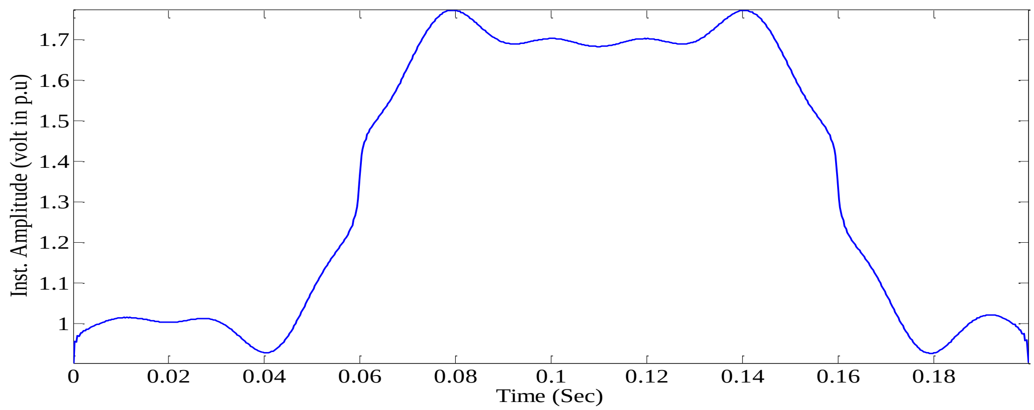


Fig. 2.3 (c) Instantaneous Amplitude (IA) vs. Time plot of swell signal

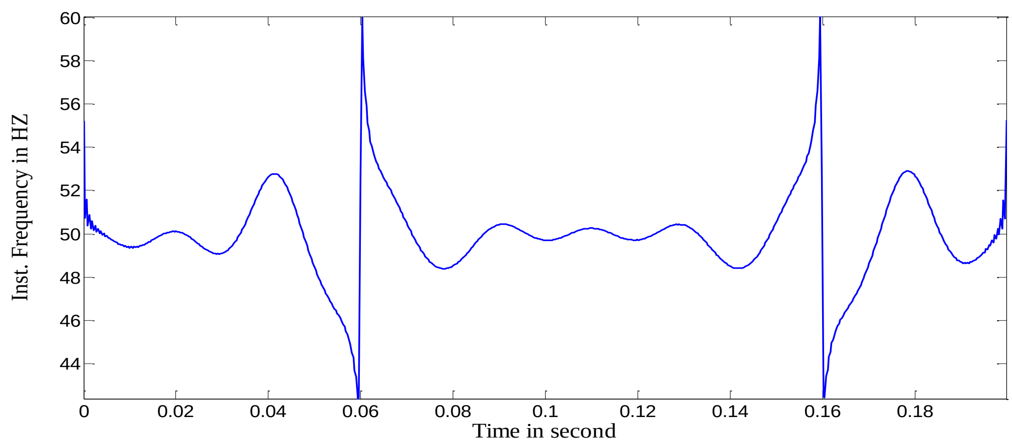


Fig. 2.3 (d) Instantaneous Frequency (IF) vs. Time plot of swell signal

2.9.3 Voltage harmonic signal

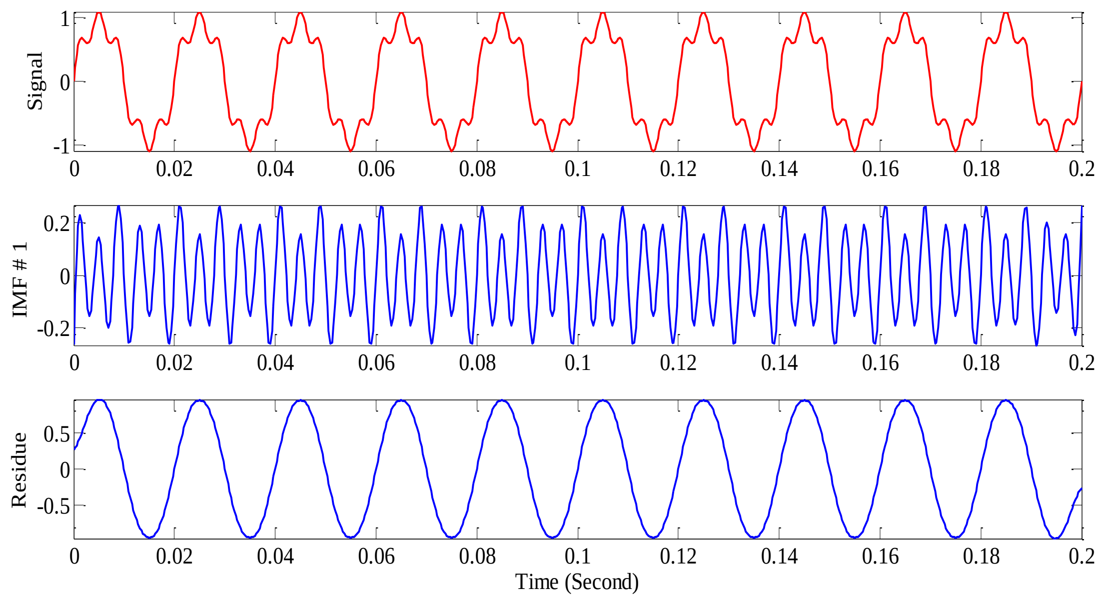


Fig. 2.4 (a) IMFs functions with residue of harmonic signal plot

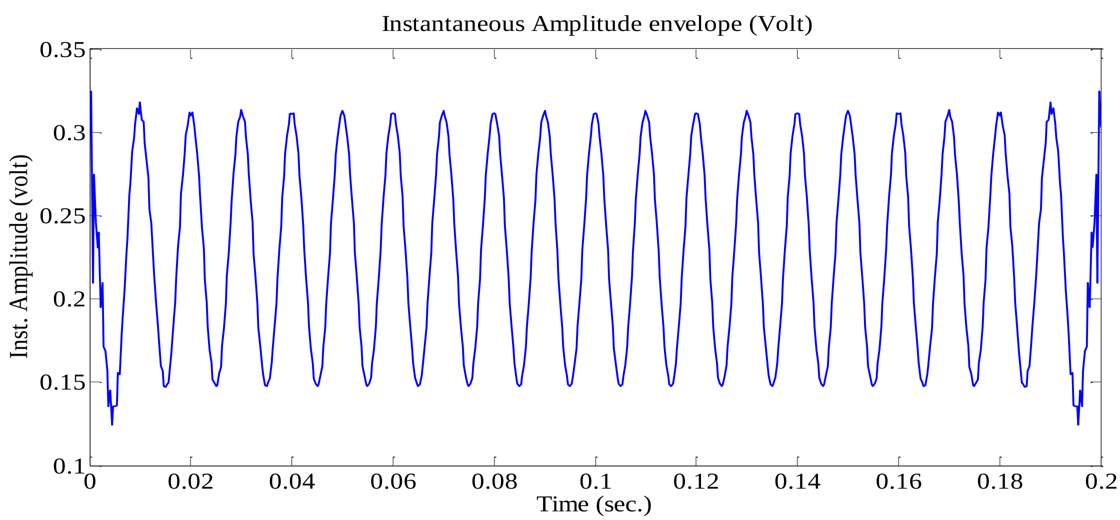


Fig. 2.4 (b) Inst. Amplitude vs. Time plot of harmonic signal

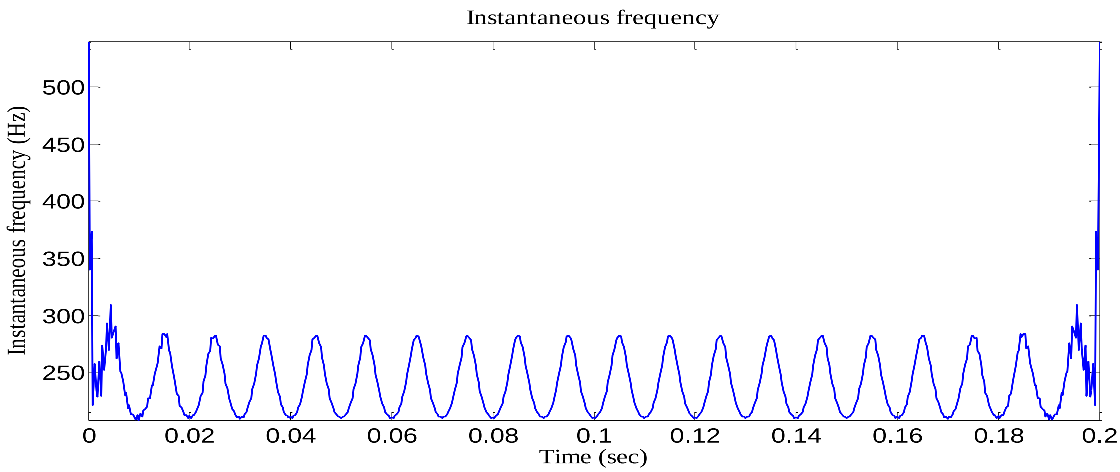
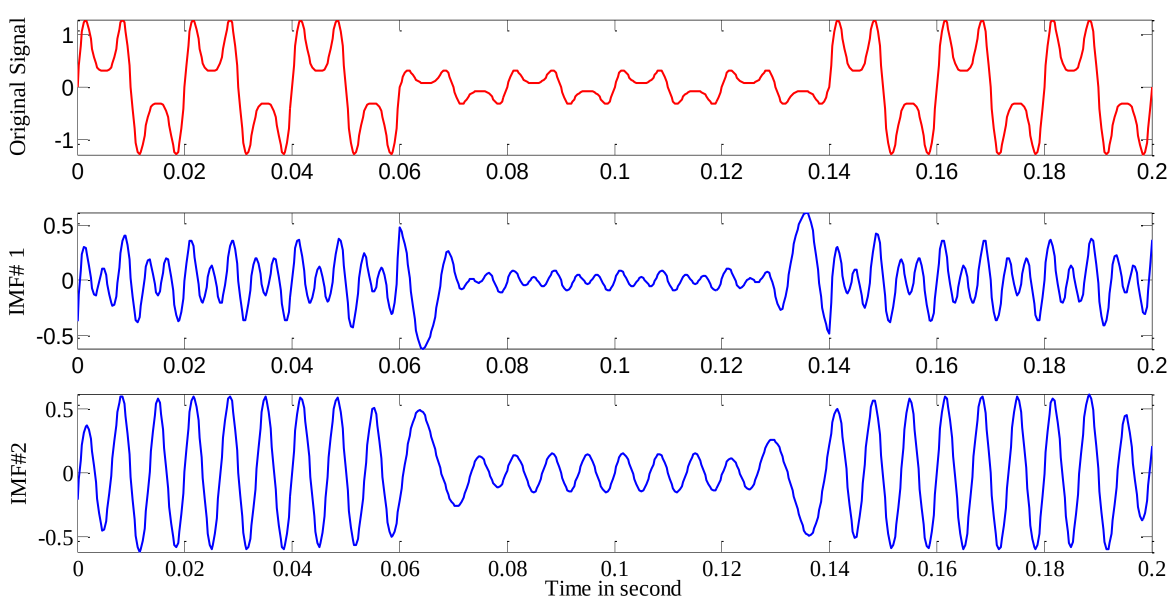


Fig. 2.4 (c) Inst. Frequency (IF) vs. Time plot of harmonic signal

2.9.4 Voltage sags with harmonics

The compound disturbances like Sag with harmonics and Swell with harmonics can also be effectively detected using the Empirical mode decomposition technique. Fig. 2.5 shows the decomposition and detection of Sag with harmonics. Here only third harmonic component is added to the fundamental component of voltage sag to obtain the voltage sag with harmonics. Similarly, other harmonic components may be added and can be detected using HHT. Figure 268 shows different IMF functions after decomposition of swell with harmonic signal.



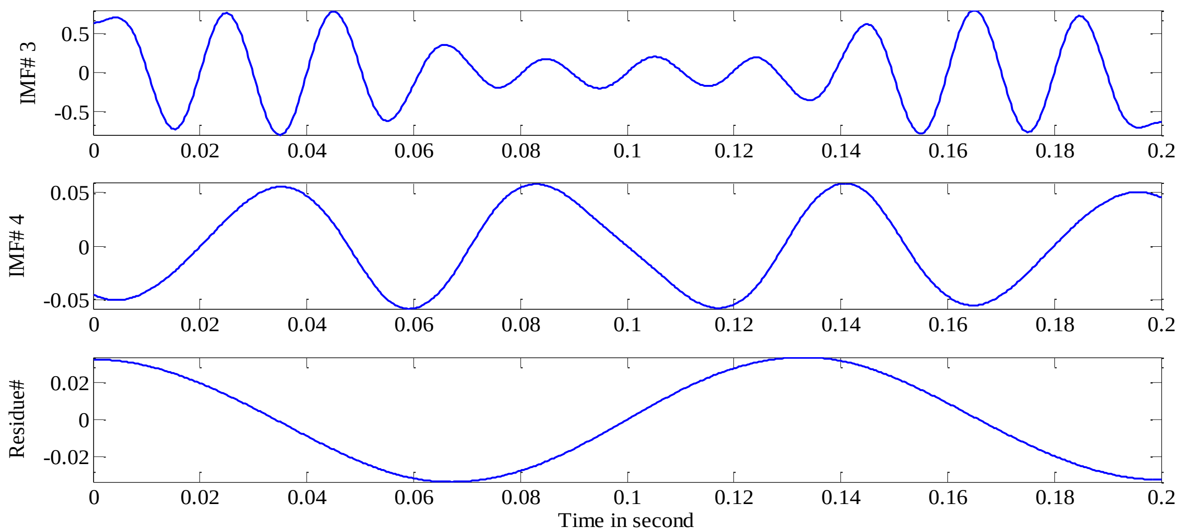


Fig. 2.5 (a) IMF functions of voltage sag with harmonic signal

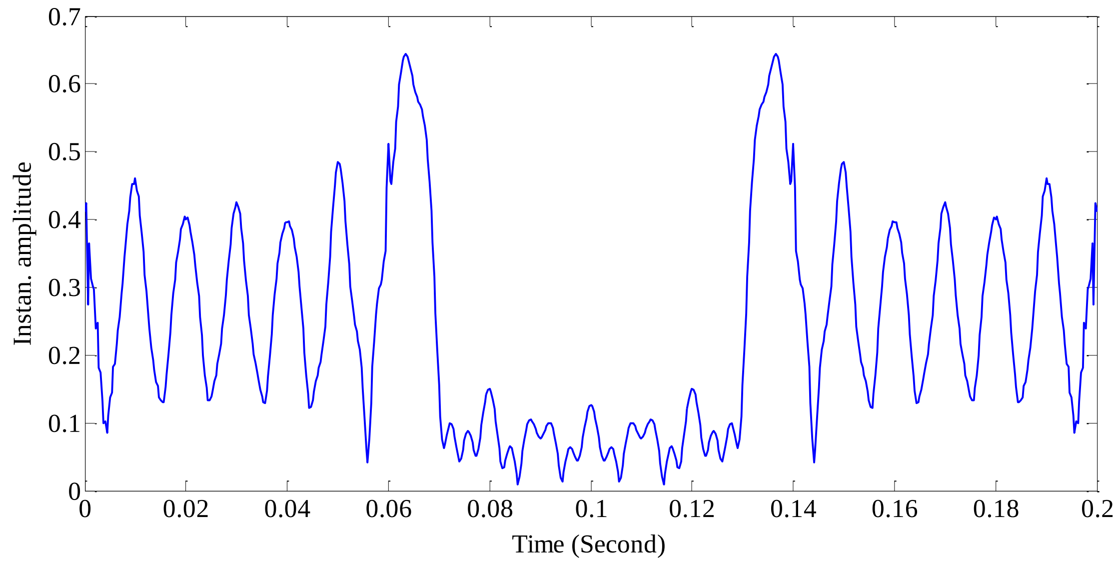


Fig. 2.5 (b) Inst. Amplitude (IA) vs. Time of the sag with harmonic signal

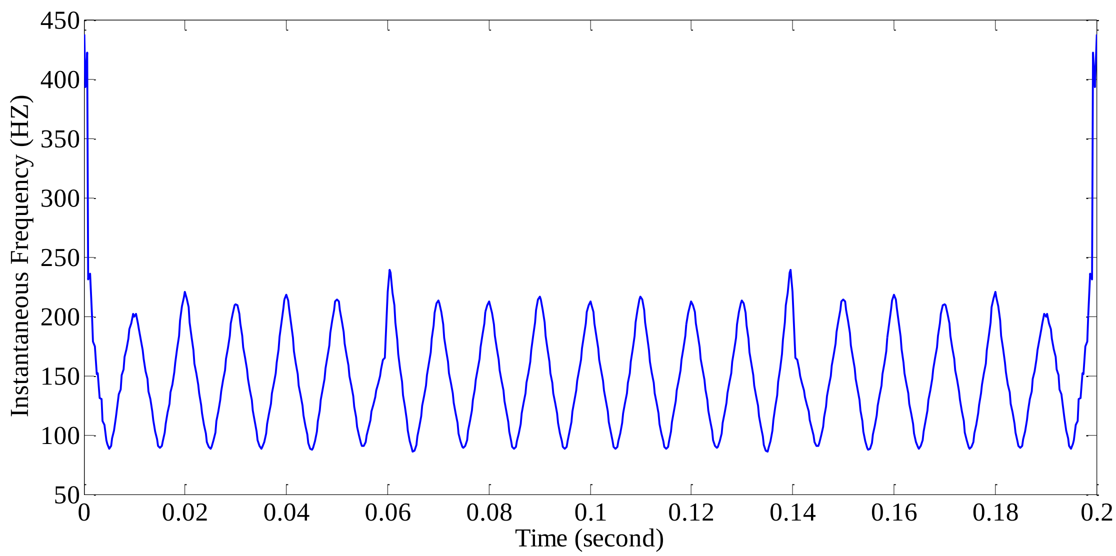


Fig. 2.5 (c) Instantaneous Frequency (IF) vs. Time plot of the sag with harmonic signal

2.9.5 Voltage Swell with Harmonics

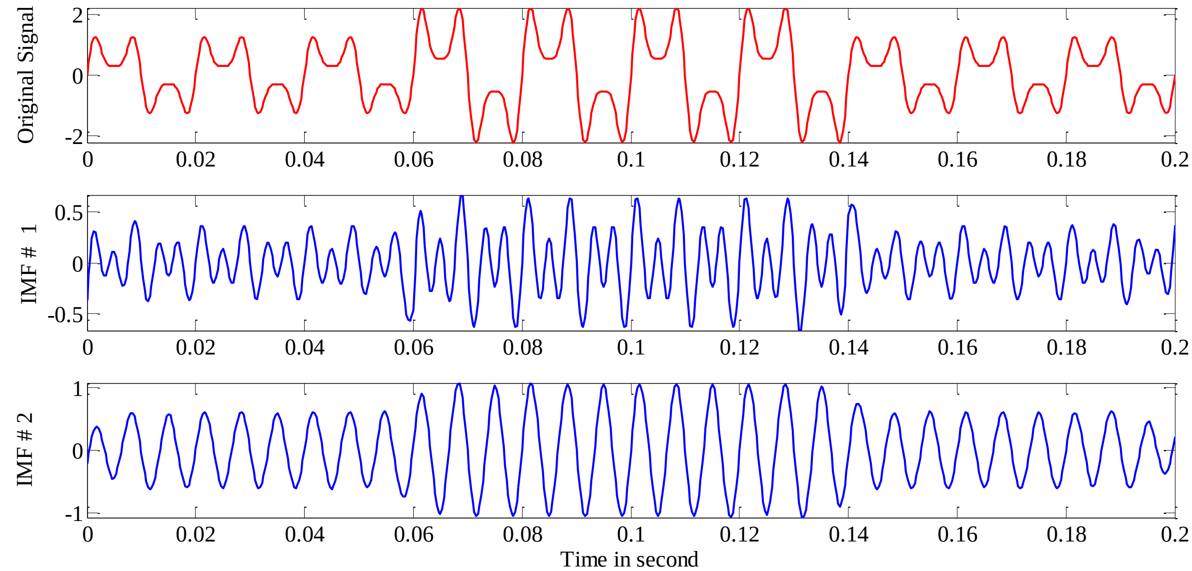


Fig. 2.6 (a) IMF1 and IMF2 functions of the swell with harmonic signal

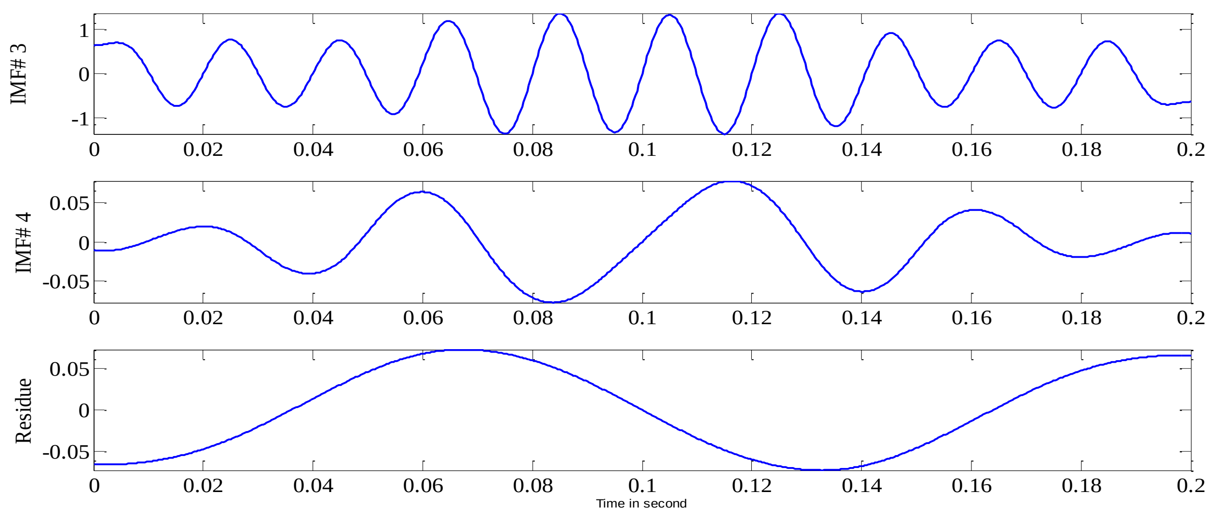


Fig. 2.6 (b) IMF3 & IMF4 of the swell with harmonic signal

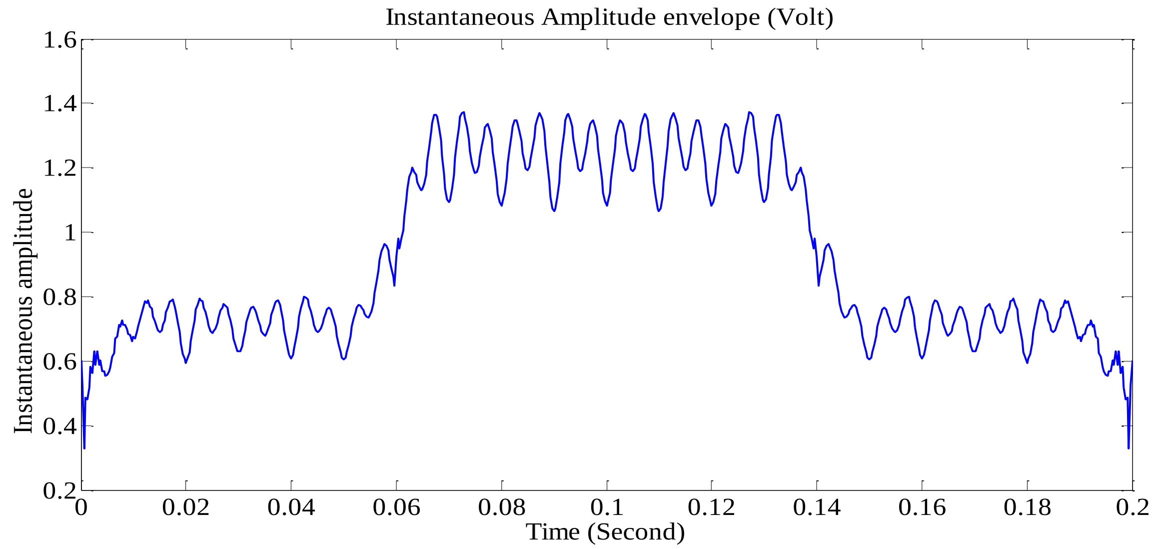


Fig. 2.6 (c) Inst. Amplitude (IA) vs. Time plot of swell with harmonic signal

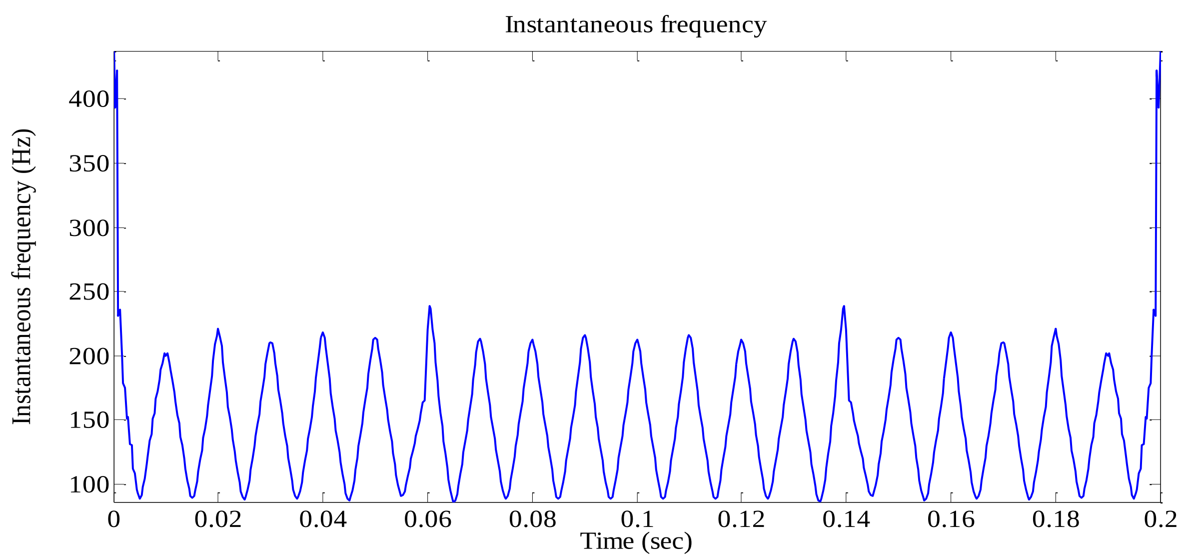


Fig. 2.6 (d) Inst. Frequency (IF) vs. Time plot of swell with harmonic signal

2.9.6 Voltage interruption

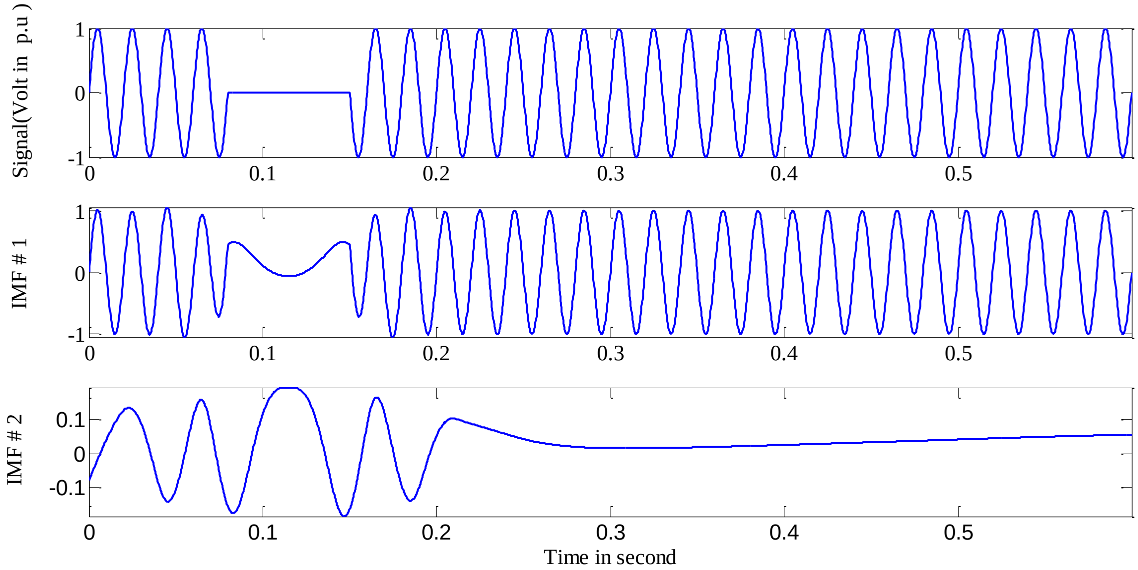


Fig. 2.7 (a) IMF1 & IMF2 function plot

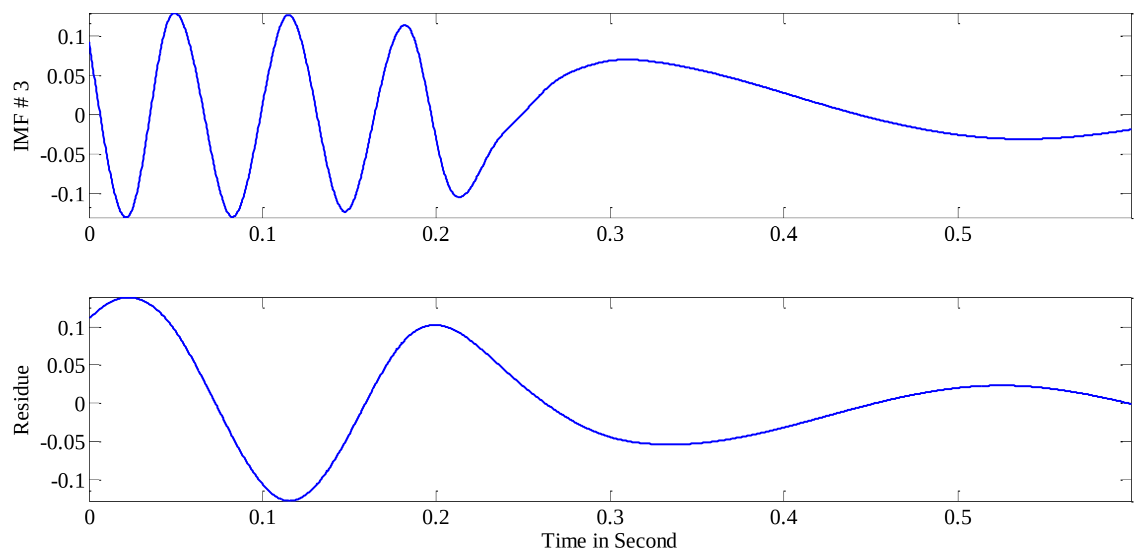


Fig. 2.7 (b) IMF3 & residue functions and residue plot

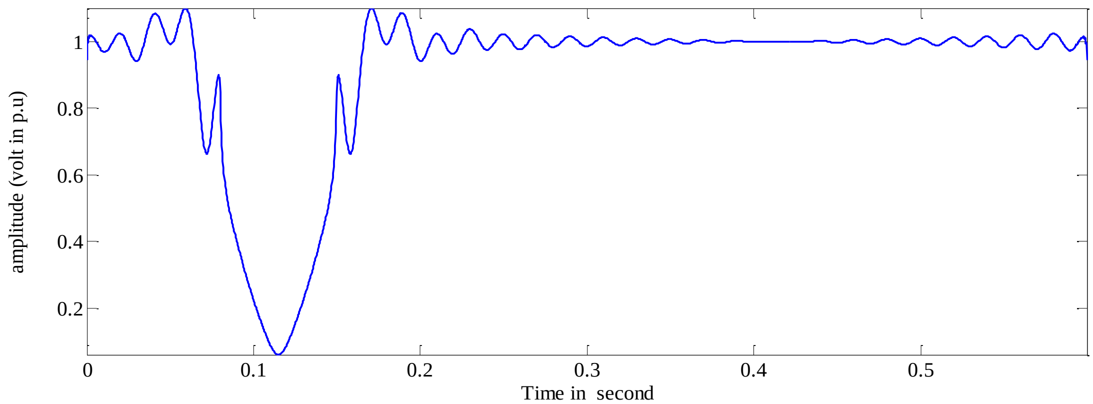


Fig. 2.7 (c) Instantaneous Amplitude (IA) vs. Time Plot

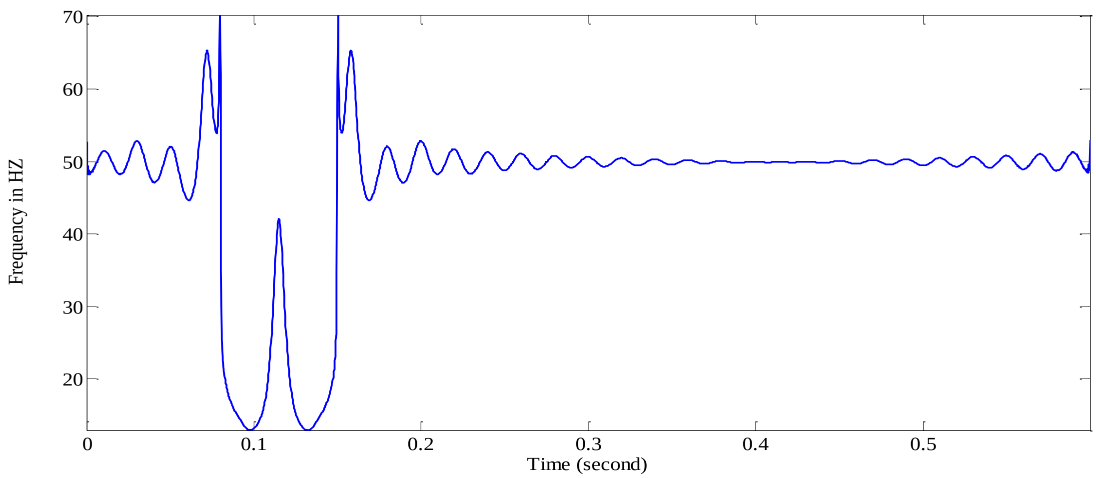


Fig. 2.7 (d) Instantaneous Frequency (IF) vs. Time Plot

2.10 Maximum Overlap discrete wavelet transformation (MODWT)

The power system signal multi resolution analysis (MRA) can be performed by wavelet technique known as maximum overlap discrete wavelet transform (MODWT). MODWT is based on filtering operations is shown the fig.2.8 which is known as 'pyramid algorithm'. The power system signal has to pass through a high pass filter and low pass filter results in detail and approximation coefficient respectively. The power system signal has to pass through a high pass filter and low pass filter results in detail and approximation coefficient respectively. After the signal passed through the filters, the approximation coefficients are obtained from the 1st level of decomposition. The approximate coefficients obtained are considered as the original signal and allowed for the next level of decomposition and gives rise to detail coefficients and approximate coefficients. MODWT is an advance version of the DWT, which does not follow the down-sampling process unlike DWT. The wavelet coefficients of the MODWT are computed in each simulation time step or soon after each sampling process. As a consequence, the power system disturbance in each event can be detected faster by using the MODWT [13].

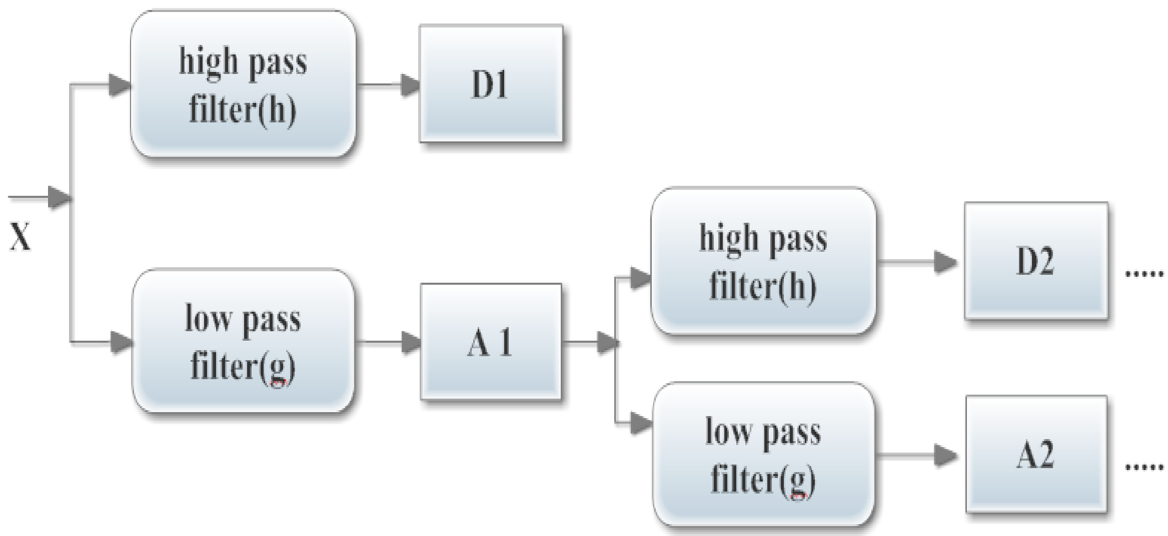


Fig. 2.8 Block diagram of MODWT decomposition technique

The fig. 2.8 shows the block diagram for decomposition of signal by MODWT, X defines the input signal samples (power system signal), D1, D2….are the each level decomposed detail coefficients and A1, A2… are the each level of approximation coefficients.

The presence of orthogonal property (signal is decomposed into atomic functions) in the MODWT gained new features. This transform does not have allows any number of sample size and it is shift invariant**.** As a result, in the MODWT, the wavelet and scaling coefficients must be rescaled to retain the variance preserving property of the DWT. Although the components of MODWT are not mutually orthogonal, their sum is equal to the original time series**.** The detail and approximate (smooth) coefficients of a MODWT are associated with zero phase filters. Furthermore, circularly shifting is possible to the original time series in case of MODWT. Where DWT does not hold good this property because of the subsampling involved in the filtering process. However, the MODWT provides twice the amount of coefficients to be analyzed in real-time (i.e. Faster real-time analysis). MODWT does not induce the phase shifts within the component series. The major advantage of MODWT among all wavelet family is that, there is no down-sampling process.

2.11 Simulation results of MODWT

The Daubechies wavelet (MODWT) comes as very powerful tool for monitoring power quality disturbances among all the wavelet families. Results of MODWT are shown in fig. 2.9 –fig. 2.13 of different PQ events. All the Simulation was done for 10 cycles with a sampling frequency of 3.2 KHz and total time period of 0.2 second. A sample of 641 data obtained is allowed to pass through the MODWT technique.

2.11.1 Voltage sags signal

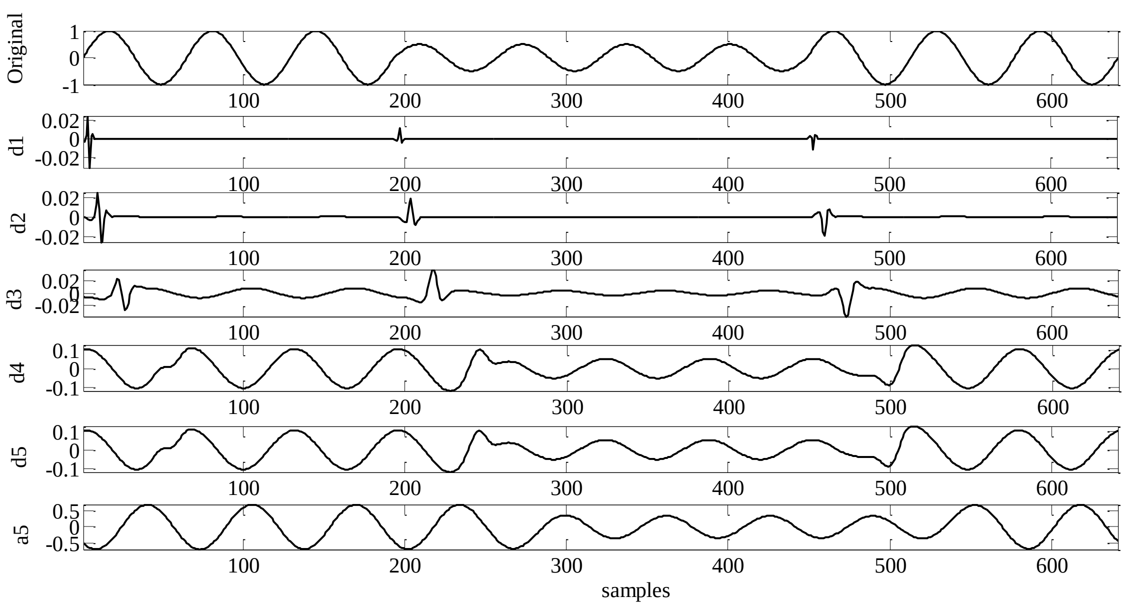


Fig. 2.9 Voltage sags signal up to the 5th level of decomposition

2.11.2 Voltage swells Signal

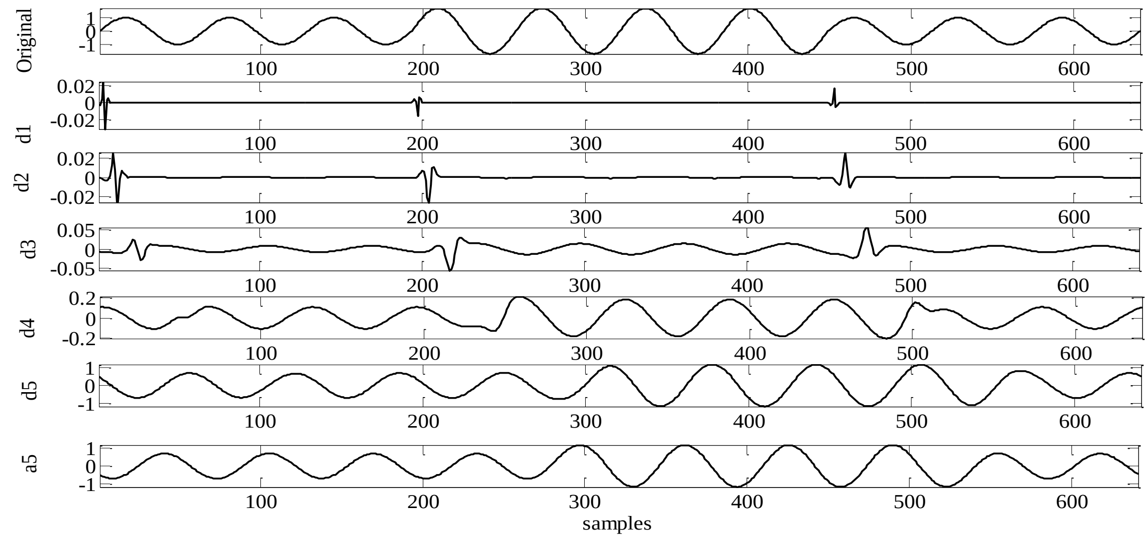


Fig. 2.10 Voltage swell signal up to the 5th level of decomposition

2.11.3 Voltage interruption signal

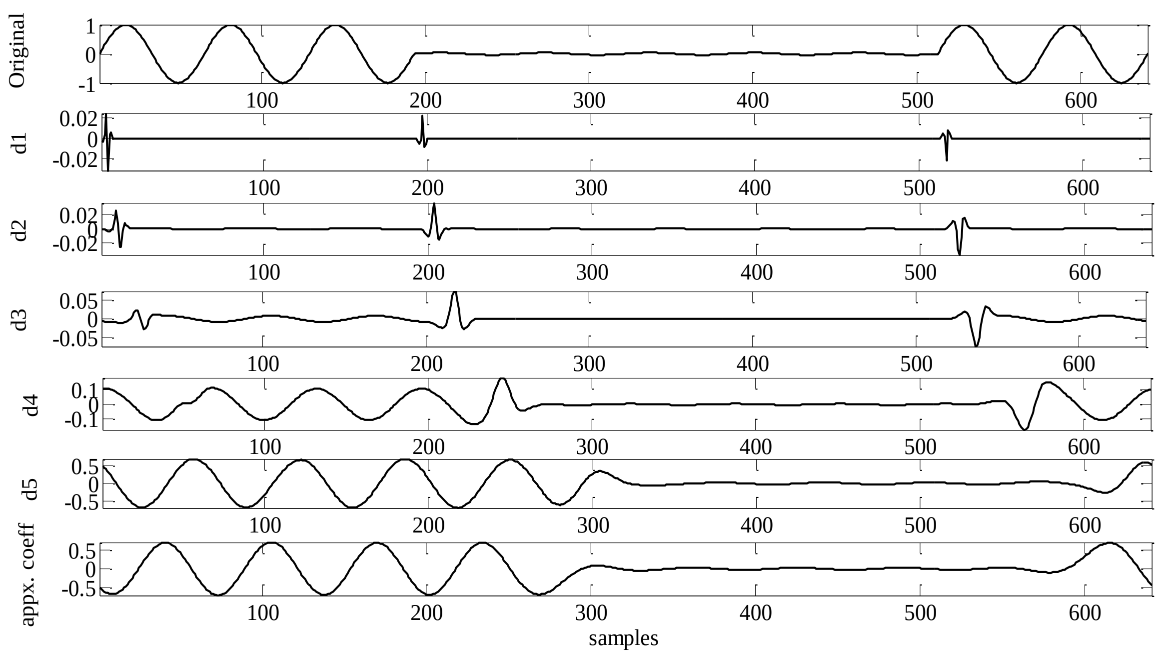


Fig. 2.11 Voltage interruption signal up to the 5th level of decomposition

2.11.4 Voltage flicker signal

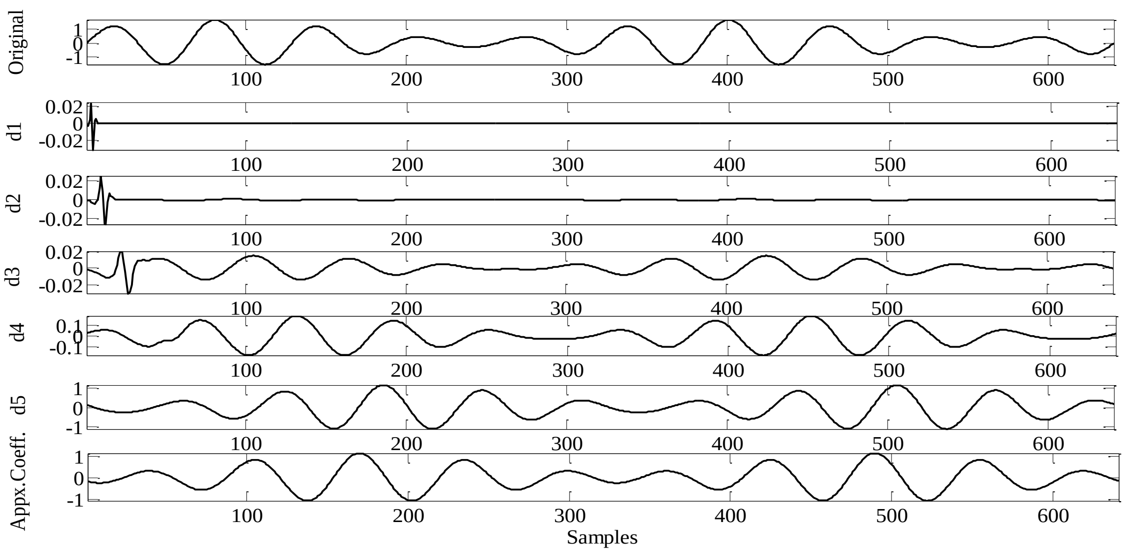


Fig. 2.12 Voltage flickers signal up to the 5th level of decomposition

2.11.5 Voltage oscillation signal

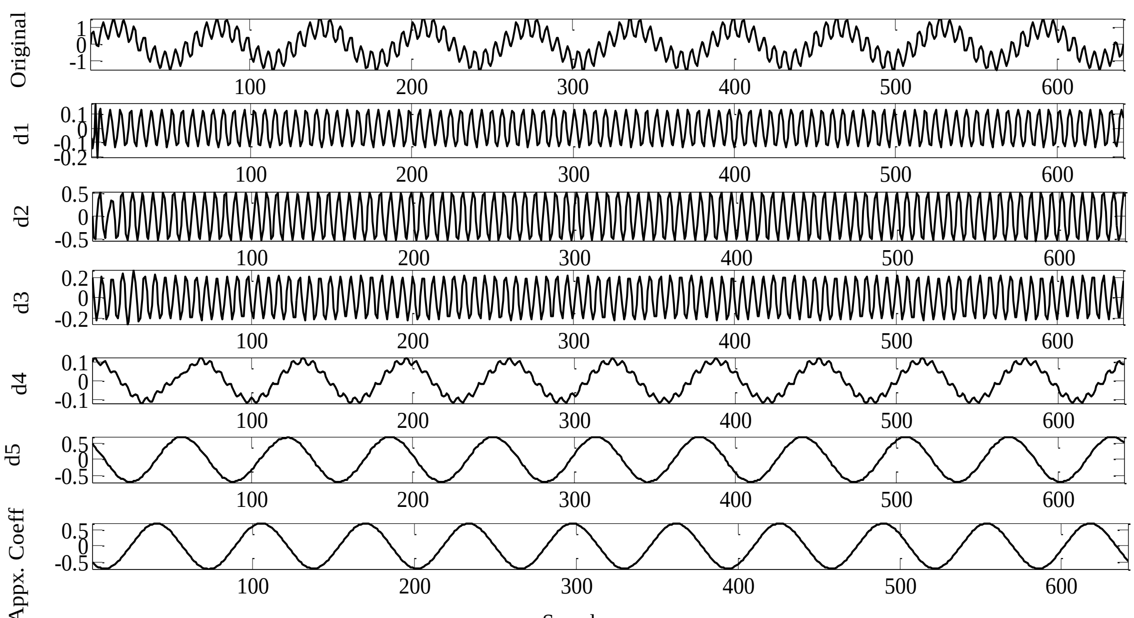


Fig. 2.13 Voltage oscillation signal up to the 5th level of decomposition

2.12 Summary

From the above decomposition results obtained from HHT tool gives a clear visualization of the point of disturbances. Hence, it’s very easy to find the time of fault. The IMF function obtained from EMD has been passed to Hilbert transform in order to instantaneous frequency and instantaneous amplitude which is use full in the extraction of feature vectors. Here the instantaneous amplitude and instantaneous frequency have been found which is very useful in case of non-stationary signal. Since there is no down sampling in case of MODWT, decomposition results does not lose any information regarding signal. This from the results we can clearly see there is no decrease in the number of samples. But wavelet transform does not work in noisy environment which is a major drawback of MODWT. Each Power quality event was passed through the wavelet decomposition technique and results were obtained employed effectively for monitoring power quality events. This results shows that MODWT provides the time-scale analysis of the non-stationary signal where HHT provides time-frequency representation.

CHAPTER # 3

Power Quality Events classification using neural network

3.1 Introduction to Classification

Feature extraction provides information about the distorted signal that helps for further investigation like classification of power quality disturbance. So any advance and accurate feature extraction technique can be useful for monitoring and maintaining power disturbances more efficient. The feature vectors are extracted from the instantaneous amplitude and the instantaneous frequency of the distorted waveforms. Disturbances like sag, swell, and their associated waveforms give more than one IMF functions, but certain PQ events like harmonic or flicker have only one mode of decomposition. Only first three IMFs of the signal provides the meaningful information because most frequency content lies within the first three modes of oscillation or IMFs. Therefore first three IMF is used for feature extraction. In case the disturbances like harmonics where only one mode of oscillation, the rest of two modes of oscillation are taken as zero. From the above decompositions results obtained in this work it is evident that the as a HHT tool is better as compared to the wavelet technique for detecting PQ disturbances works very well and can be employed effectively for monitoring power quality events.

After passing each IMF function through each of the Hilbert transformed analyses following three features were extracted.

1) Energy distribution corresponding to magnitude of the Hilbert analysis for each type of power signal.

2) Standard deviation of the amplitude and frequency feature vectors

3) Entropy of the amplitude and frequency feature vectors.

Thus, in all, three features are extracted. The block diagram shown Fig. 3.1 gives brief overview of the process of feature extraction from distorted waveform.

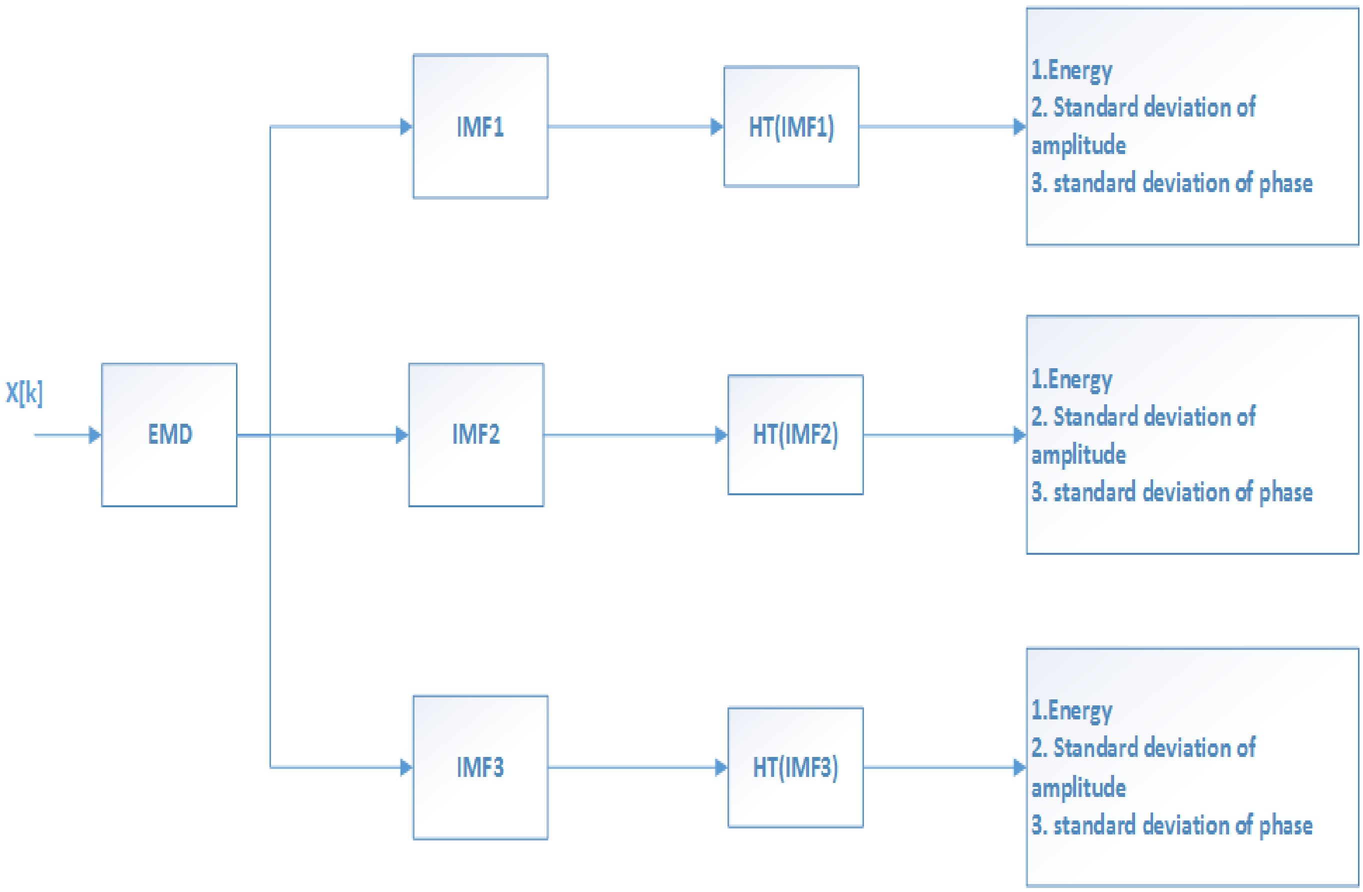


Fig. 3.1 Block diagram of feature extraction

3.1.1 Standard deviation

The standard deviation gives information about multi resolution analysis of each level IMFs. A standard Deviation is always a positive quantity. In order to extract features of power system Signals, the standard deviation of power quality problem Signals is subtracted from the standard deviation of pure Sinusoidal waveform.

For non-stationary frequency data, standard deviation can be given as

$$Standard\ deviation = \sqrt{\frac{\sum_{i=1}^{N}(X_i - \bar{X})}{N}} \tag{3.1}$$

Where, X_i are non-distributed frequency data

$\overline{X}$ Is mean of data and N is number of data.

3.1.2 Energy of the signal

The energy of a signal is calculated using parse Val's theorem [10] which states that if *v (t)* is the voltage across the resistor or current through the resistor then the energy dissipated is

Energy value of frequency of signal is given as

$$\text{Energy} = norm(IF)^2 \tag{3.2}$$

3.1.3 Entropy of the signal

The feature entropy of a signal is helpful to represent the characteristics of the signal and measure the uncertainty of information and events. HHT entropy is used for the analysis of power quality disturbances.

The Shannon entropy of a discrete random variable X and probability distribution P is given as

$$H(x) = -\sum_{i=1}^{N} P \;\; P_i \log(P_i) \tag{3.3}$$

Where Pi is the probability of the system.

3.2 Power Quality events classification using BPA in multilayer feed-forward neural network

Neural Networks (NN) are one of the most widely adoptable data mining techniques used for classification and clustering. In this work most simple and popular NN has been used known as Back Propagation (BP) Algorithm. The BP algorithm is very simple and output of NN is evaluated against desired output. If error results are not satisfactory, connection weights between layers are modified and process is repeated again and again until error is small enough.

Back Propagation algorithm is a feed forward neural network. Rojas [2005] has divided the BP algorithm into to four steps. First of all the weights matrix of the network is chosen randomly, the back propagation algorithm is used to compute the necessary corrections. The four necessary steps of BP algorithm:

i) Feed-forward computation

ii) Back propagation to the output layer

iii) Back propagation to the hidden layer

iv) Weight is updating

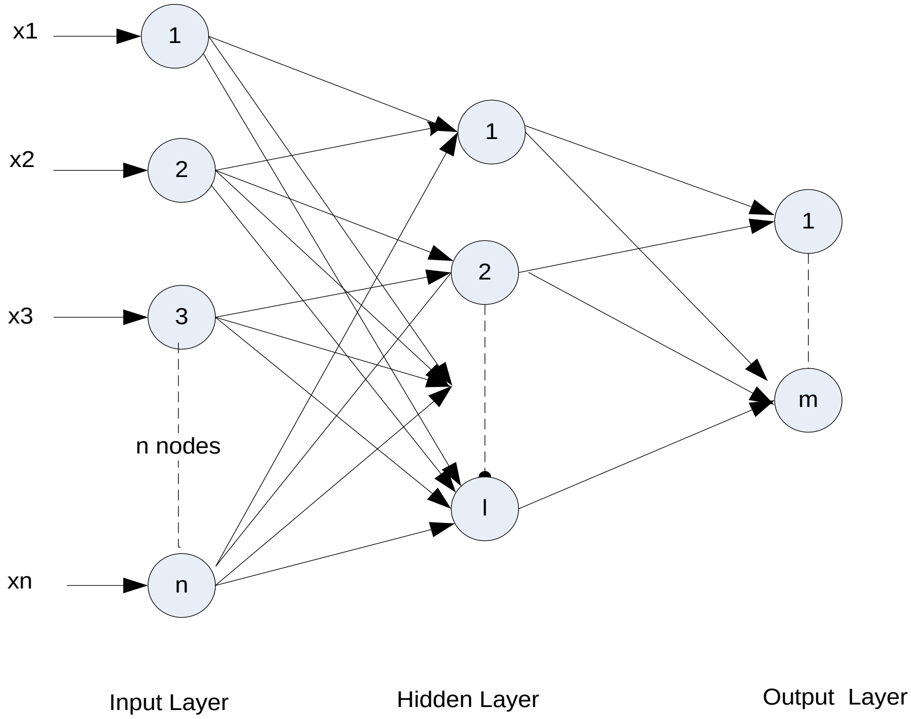


Fig.3.2 Block diagram for multilayer feed forward neural networks

In BP Algorithm is the weight adjustments are done based on a delta learning rule. The set of these sample patterns are repeatedly iterated in the network until the error value is minimized. Here three features such as the standard deviation, energy and the entropy of each of the distorted Power signals and also of the normal voltage signal are considered as inputs to the MFFN. Activation functions used for both input and hidden layer are same, i.e. Sigmoidal Activation function. BP Algorithm has been used for the classification in ordered to find out classification accuracy (CA). In this work each PQD is classified with the pure sine wave. The features are extracted from each IMF after the signal passed through Hilbert transforms. To achieve better classification, data input to the model should be proper and optimum neural network structure and correct training of BPA network with suitable parameters is necessary.

3.3 Algorithm of multilayer feed-forward neural network for PQ event Classification

Algorithm (multilayer feed-forward neural network)

Step1. The feature vector obtained from extraction process are first normalized and then selected as input to the model.

Step2. Each decomposed signals are allowed to pass neural network model. Random weigh is taken between hidden to output layer and input to output layer for Initialization of neural network model.

*Step3. For training purpose, 25 samples from each signals has been selected, so that total of 5*25= 125 samples of data from five signals is collected for training.*

Step4. Output obtained from the input node is directly feed to the hidden layer and output obtained from hidden layer and output of output layers are evaluated by using sigmoid activation function.

Step5. This process continues from Step1 to step4 till convergence occurs.

Step6. After convergence the weights obtained are considered as the final weight and are collected in a data sheet.

Step7. For testing the network model 50-60 feature vector samples are given as input to NN model. The output is used for calculation of classification accuracy.

3.4 Neural network results and discussions

Total 180 samples, 125 for training and 65 for testing are considered in each case. The structure of this BPA is 12-5-3.Average classification accuracy has been calculate.

The classification accuracy is evaluated as per the given equation

$$\text{Classification Accuracy (\%)} = \frac{\text{No. of samples correctly classified}}{\text{Total no. of samples in the data set}} \times 100 \qquad (3.4)$$

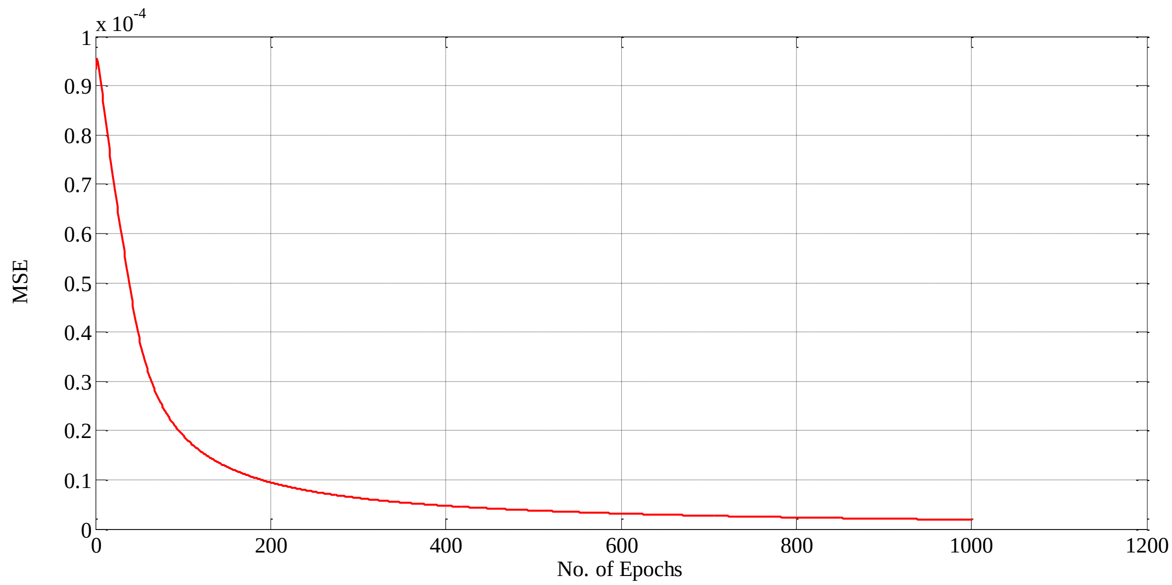


Fig. 3.3 MSE vs. No. of epochs plot using HHT

The fig. 3.2 shows a MSE= 1.889e-04 for 1000 epochs with corresponding eta= 0.028, alpha= 0.45

The classification accuracy with multilayer feed-forward neural network with sigmoidal activation function in hidden layer units shown in fig.3.3 (g).The Estimated has an error of around 1.45e-4 percent.

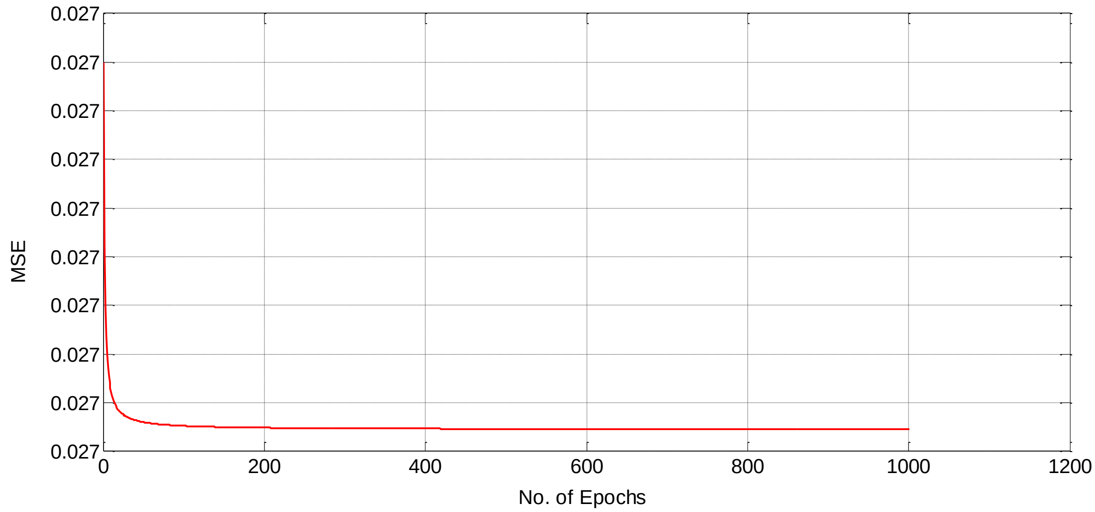


Fig. 3.4 MSE vs. No. of epochs plot using MODWT

The classification accuracy with multilayer feed-forward neural network with sigmoidal activation function in hidden layer units shown in fig.3.3 (g).The Estimated has an error of around 0.027%.

The output of BP Algorithm Mean Square Error (MSE) at different eta and alpha values for 1000 epoch is presented in Table 3.1.

Table 3.1 MSE values with different values of eta and alpha using HHT

Sl no.	eta	alpha	MSE
1	0.02	0.4	5.497e-07
2	0.025	0.5	3.174e-07
3	0.03	0.55	2.306e-07
4	0.035	0.6	3.595e-06
5	0.04	0.45	4.0104e-06

The performance index of this method for classification accuracy of PQ can be calculated through mean absolute error (MAE), defined as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}| x_i - y_i | = \frac{1}{n}\sum_{i=1}^{n}| e_i | \qquad (3.5)$$

Where y= estimated class type through multi-layer FFNN.

y= Actual class type

n= Number of observations

And e=error signal generated

Table 3.2 Classification results

SI no.	HHT	MODWT
MAE	3.465%	4.94%

3.5 Summary

Instantaneous amplitude (IA) and instantaneous frequency (IF) are obtained from Hilbert transform. In this chapter different feature vectors like standard deviation, energy, and Shannon's entropy are extracted from both the techniques. Multilayer feed forward neural network is used for the classification of five PQD events. Both in HHT and MODWT the feature vectors are used as input to the data for training purposes and percentage of voltage disturbance is estimated and based on this percentage of disturbance the type of disturbance can be easily found out. MSE vs. Time plot for both HHT and MODWT technique has been shown in this chapter. The results obtained are quite satisfactory, which is evident from the low value of the mean absolute error (MAE) obtained in testing of the PQD detection system, but MFFN takes longer time for training if data sheet contains more number of data because it works on iterative procedure.

CHAPTER # 4

Conclusion and suggestions for future scope

4.1 General Conclusion of the Thesis

The Power quality monitoring is an important issue before mitigation because types of disturbance and fault localization must be known in order to take any corrective measure. Therefore PQD Detection and classification is the very important aspect for power quality. In this thesis, six different types of PQ disturbances which includes compound disturbances such as swells with harmonic and sags with harmonic for the categorization purpose. At the First phase, these PQ disturbances are decomposed using EMD algorithm and Hilbert transforms, which is known as Hilbert-Huang transform. This works shows that the HHT is a powerful signal processing tool which is quite efficient in analyzing the non-stationary and nonlinear PQ disturbances. HHT signal decomposition technique gives a clear visualization of point of disturbance and it is also able to give the instantaneous frequency and instantaneous amplitude. Unlike any other transformation, Hilbert transformation is useful for plotting Time-frequency plot and instantaneous frequency and amplitude vs. time plot. By using HHT, Time-frequency domain approach, PQ signals are investigated at different frequency resolution levels. Different features like standard deviation, entropy, energy of the PQ events are obtained from EMD and Hilbert transform technique. A data sheet is prepared from these for further classification purpose of the PQ disturbances with various magnitudes. The classification is obtained through a suitable and simple neural network known as Multilayer Feed Forward Neural Network (MFNN).

A PQD detection system based on the MFNN is modeled. The features vectors are used as input to the training patterns and percentage of disturbance is found out and based on this percentage of disturbance the class of disturbance can be easily obtained. The mean square error and the mean absolute error are obtained in the training and the testing process respectively. These are found to be satisfactory. But MFNN is little slower and takes more time for training if the no of data are more as it is an iterative procedure. The mean square error (MSE) obtained from HHT is too low about

1.889e-4 compared to MSE obtained from MODWT is 0.027. The classification accuracy of PQ events using HHT is nearly 99.5% where classification accuracy using wavelet technique is found to be 98%. For pure signal like sags, swell and interruption the best classification result is found to be 100% because the common waveform of these types of PQ disturbance rarely changes.

4.2 Suggestions for future scope

1. In this thesis work, only three features like standard deviation, energy and entropy has been considered for modeling the PQD detection system .However more features like THD can be used for included modeling PQ detection system.

2. The classification accuracy can be compared with other neural network or fuzzy logic.

3. Both Hilbert power or energy spectrum and MODWT spectrum can be obtained for different PQ events.

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